www.bsc.es

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

Decadal/Seasonal predictability of the climate system with case studies for the North Atlantic/Arctic

Pablo Ortega

PARAMOUR

Climate Prediction Group
Earth Sciences Department

APPLICATE.eu
Advanced prediction in polar regions and beyond

EUCP
European Climate Prediction system

Seminar @ UCL – 30/11/2018

The MareNostrum 4 Supercomputer

The most heterogeneous cluster in the world aimed at generating scientific knowledge

Nearly **165,888 cores**

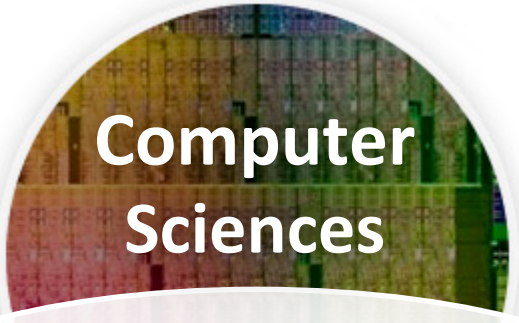
390.8 TB of main memory

3 PB of disk storage

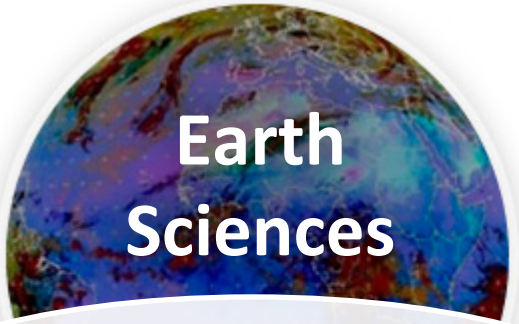
80% PRACE **16% RES** **4% BSC-CNS**

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

Mission of BSC scientific departments



To influence the way machines are built, programmed and used: programming models, performance tools, Big Data, computer architecture, energy efficiency



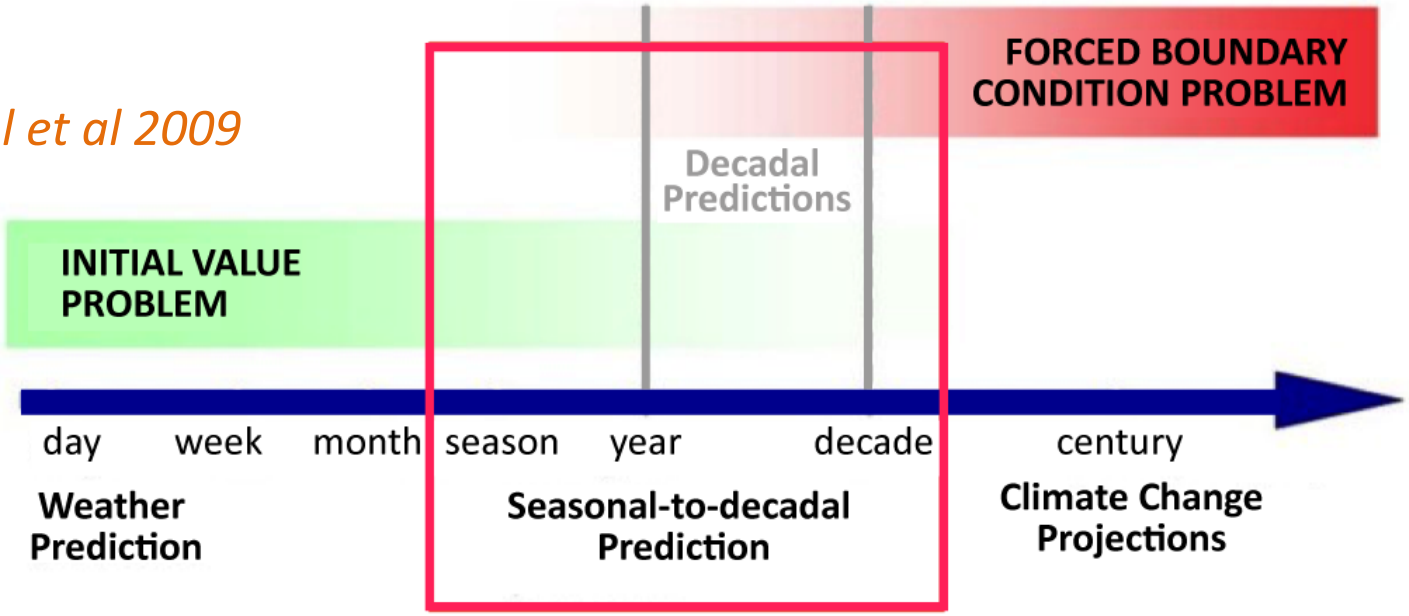
To develop and implement global and regional state-of-the-art models for short-term air quality forecast and long-term climate applications

To understand living organisms by means of theoretical and computational methods (molecular modeling, genomics, proteomics)

To develop scientific and engineering software to efficiently exploit super-computing capabilities (biomedical, geophysics, atmospheric, energy, social and economic simulations)

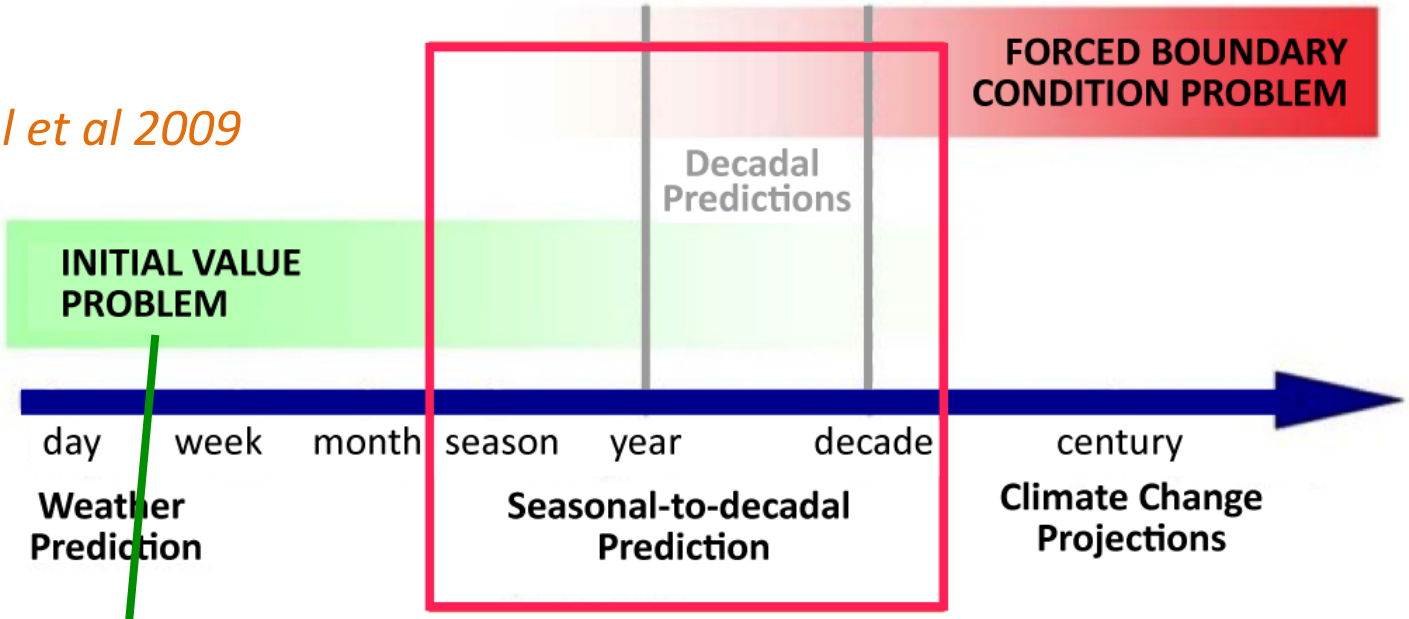
Cornerstones of Climate Prediction

Meehl et al 2009

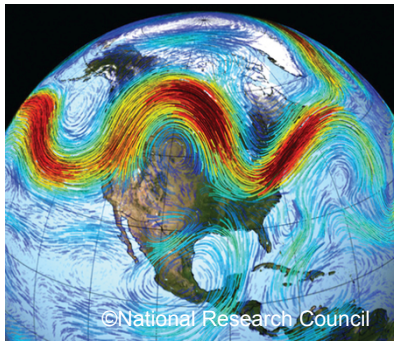


Cornerstones of Climate Prediction

Meehl et al 2009



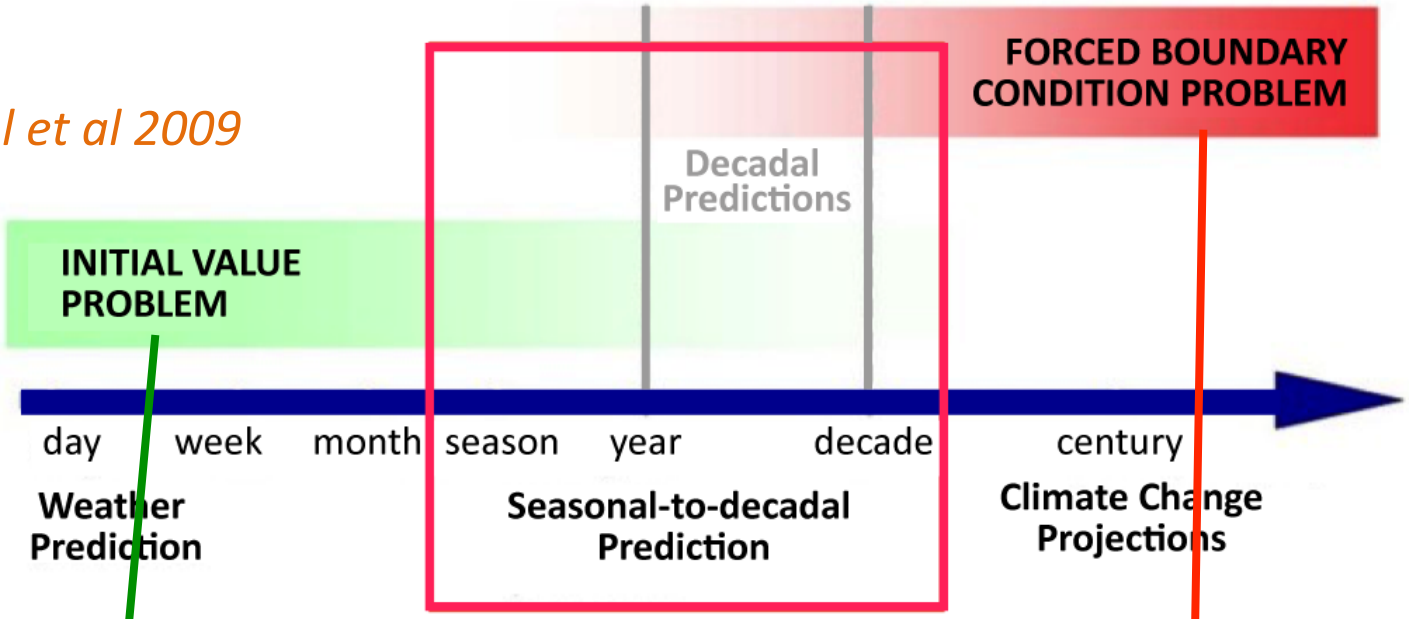
Current Meteorological state



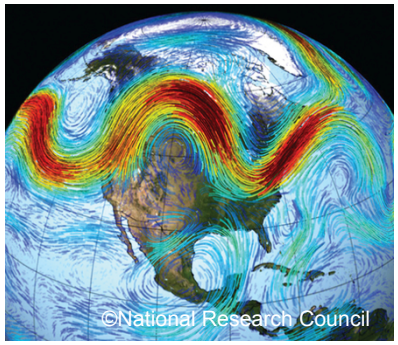
Correct Initialization of internal sources of predictability

Cornerstones of Climate Prediction

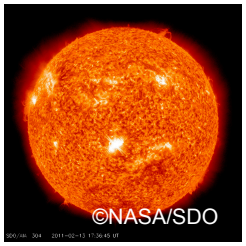
Meehl et al 2009



Current Meteorological state



Solar Activity



GHGs

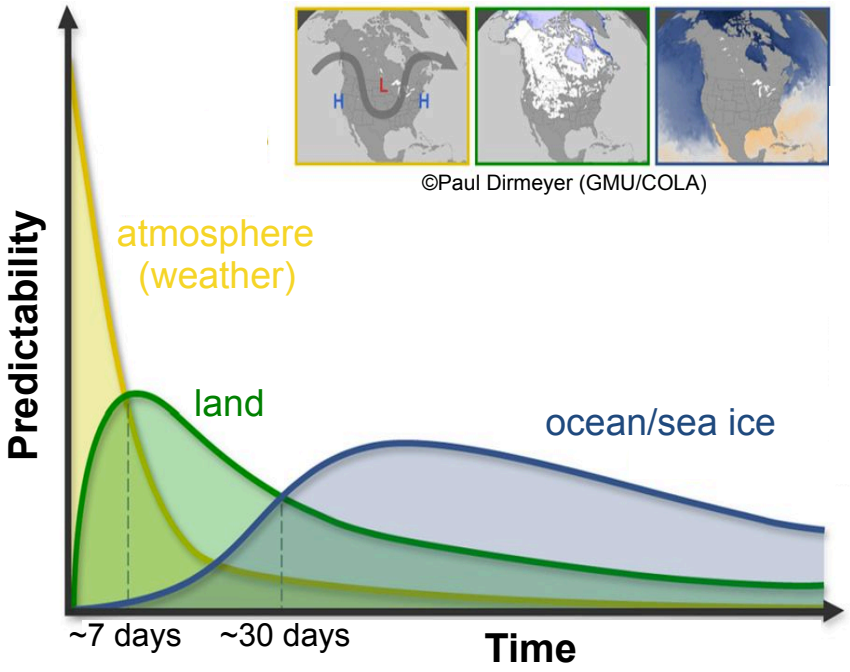
Volcanic Aerosols

Correct Initialization of internal sources of predictability

Good guess of future changes in the forcing

Internal sources of Climate Predictability

Mariotti et al 2018

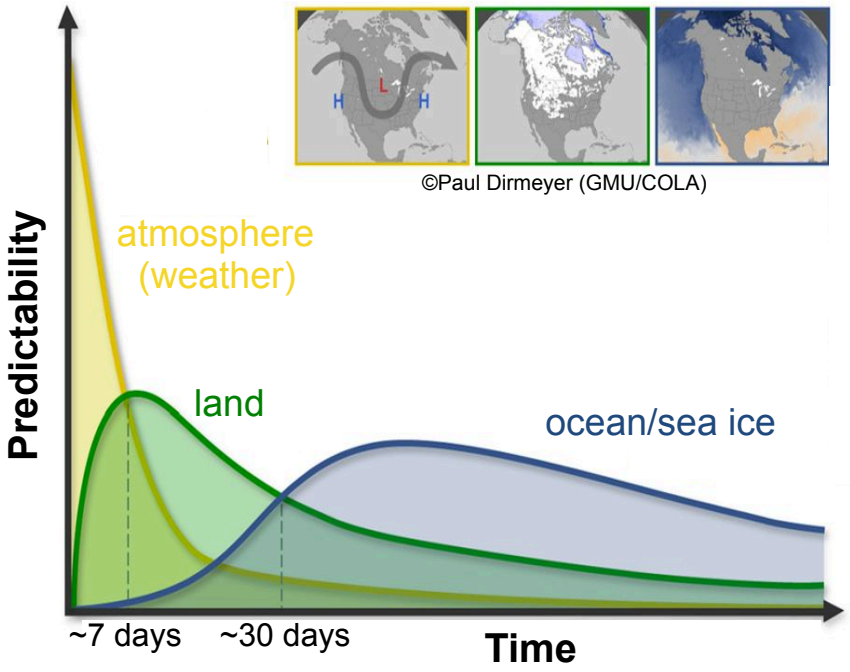


Weather prediction time horizon **~ 10 days**

Because of the chaotic nature of atmospheric variability

Internal sources of Climate Predictability

Mariotti et al 2018



Weather prediction time → horizon **~ 10 days**

Because of the chaotic nature of atmospheric variability

Climate prediction time → horizon **Weeks Decades**

It relies on the longer memory of other elements of the climate system

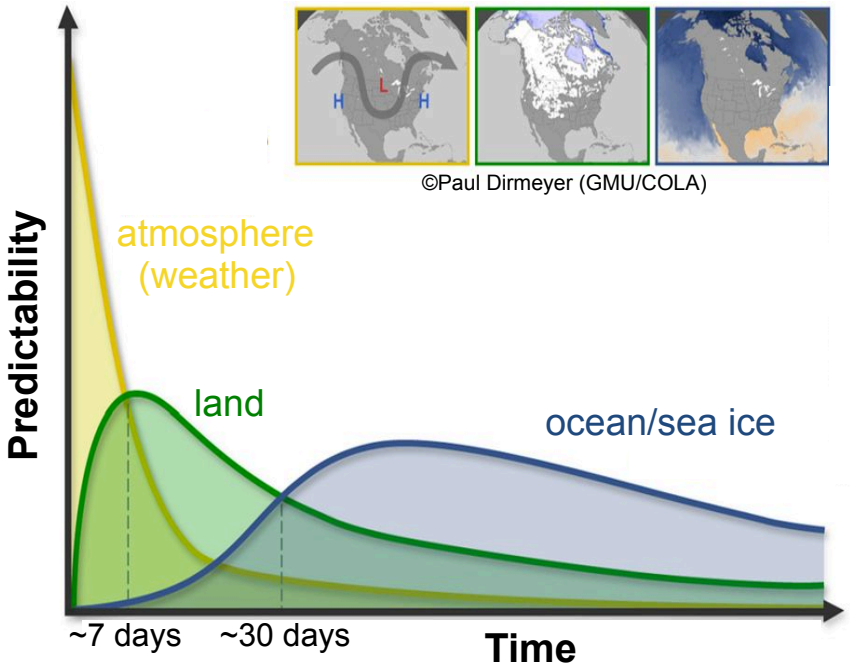
ocean

sea ice

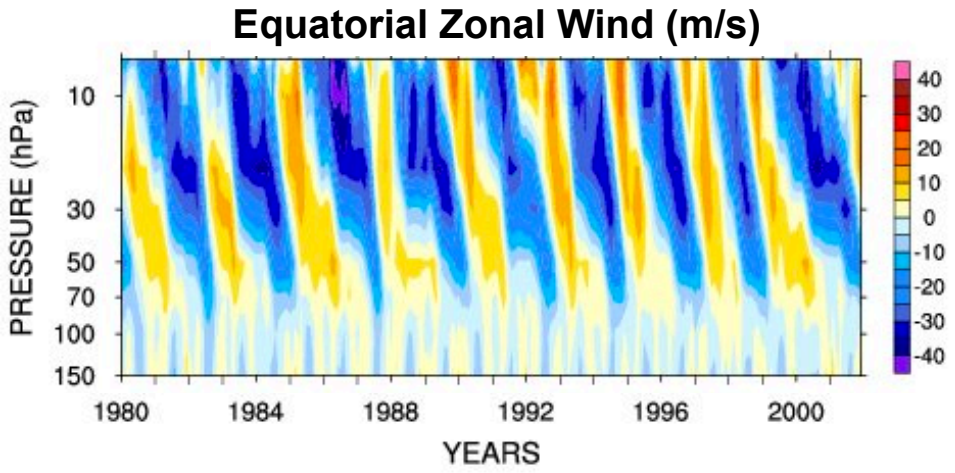
soil moisture

Internal sources of Climate Predictability

Mariotti et al 2018

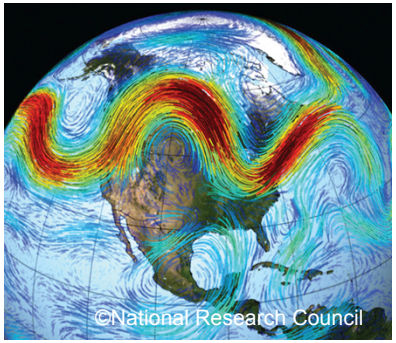


The **atmosphere** can also provide **memory** beyond monthly timescales: the **QBO**



Monier & Weare (2011)

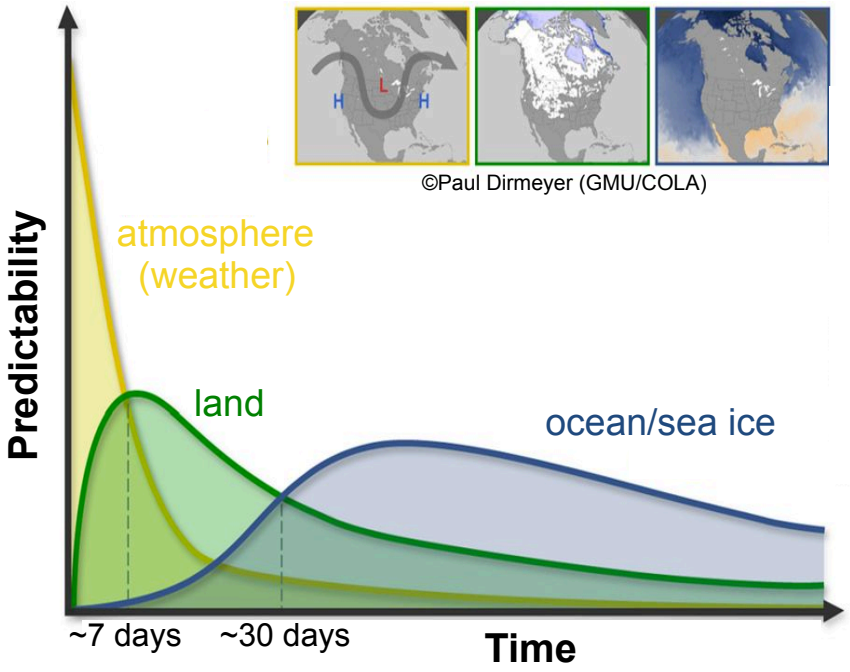
atmosphere



Through its key role on wave propagation that can further impact the polar vortex strength, the **Quasi-biennial Oscillation** can contribute to Northern Hemisphere predictability at seasonal and interannual timescales.

Internal sources of Climate Predictability

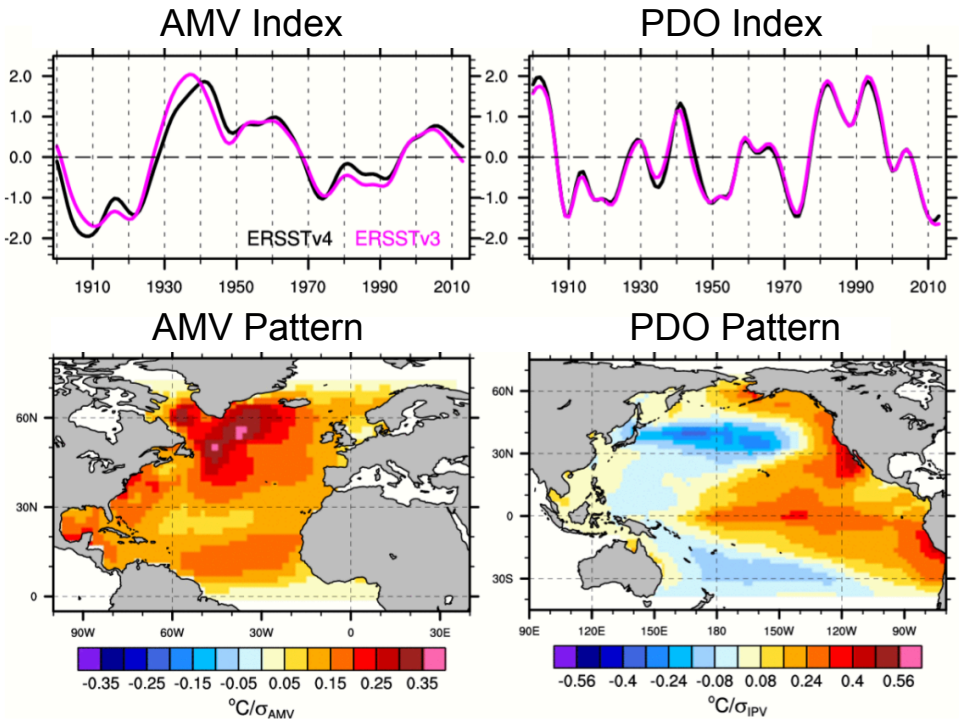
Mariotti et al 2018



©Paul Dirmeyer (GMU/COLA)

ocean

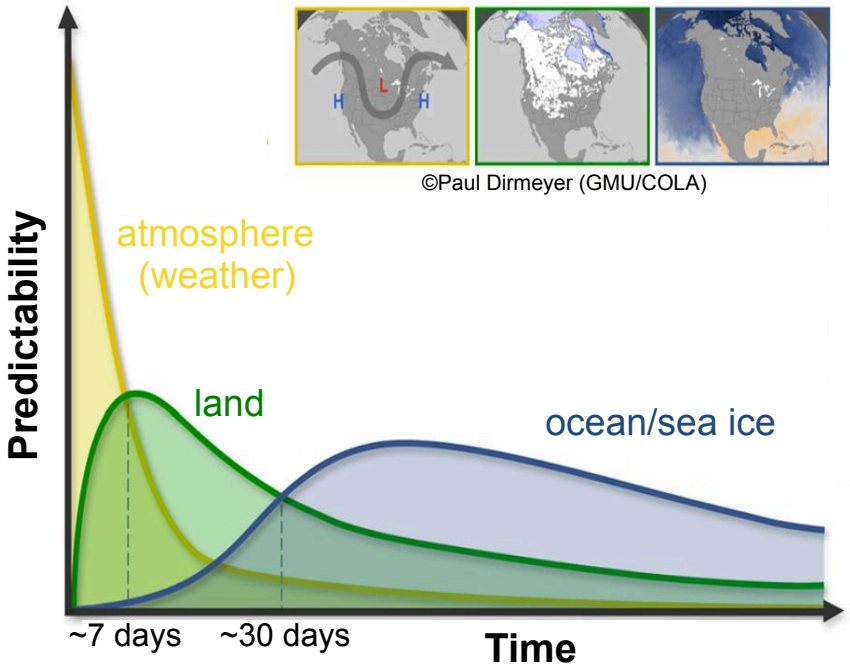
The **ocean** exhibits modes of **decadal variability** both in the **Atlantic** and **Pacific** basins



Cassou et al,
Technical Note for DCPP-Component C

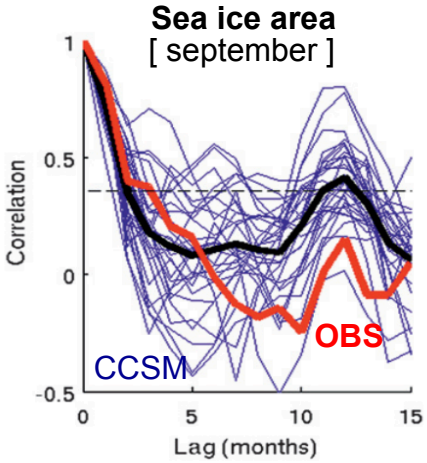
Internal sources of Climate Predictability

Mariotti et al 2018



sea ice

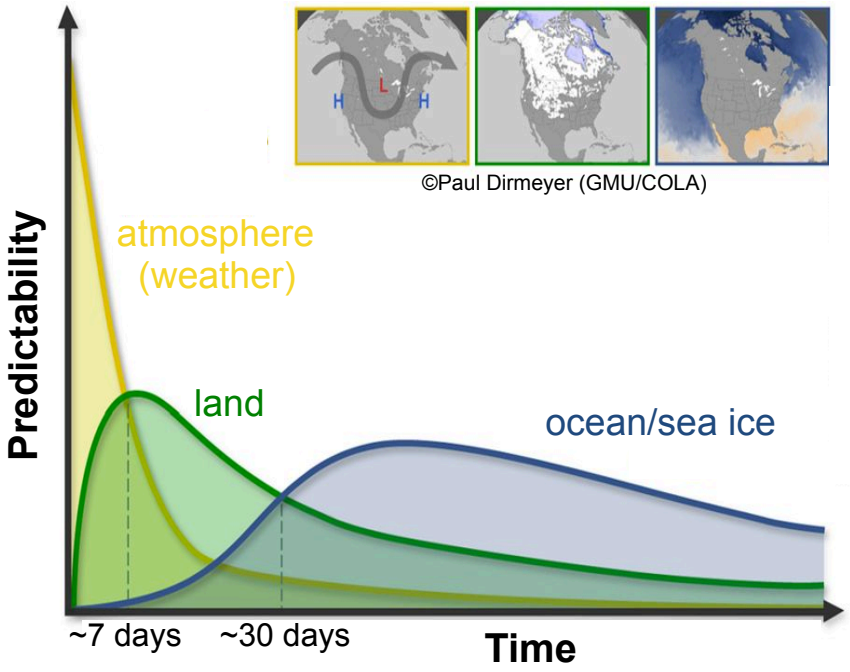
Re-emergence mechanisms in Arctic **sea ice** can provide memory and thus predictability at **seasonal scales**



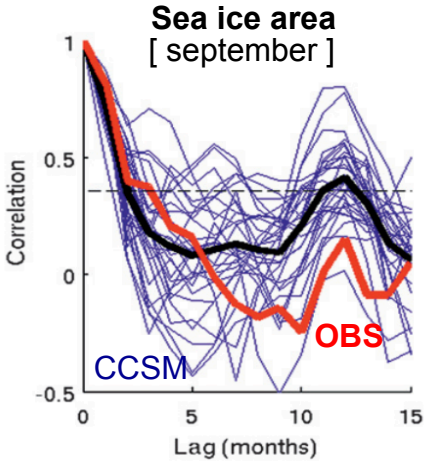
Blanchard-Wrigglesworth et al 2011

Internal sources of Climate Predictability

Mariotti et al 2018



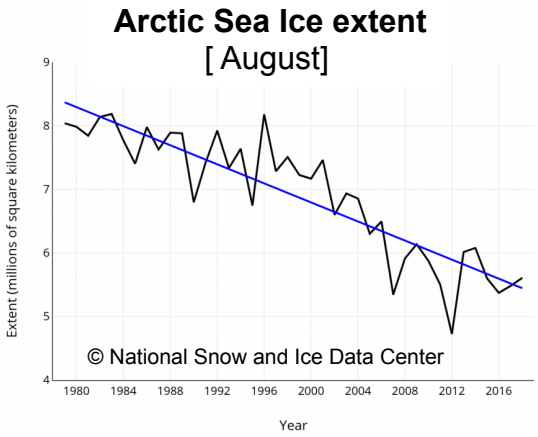
Re-emergence mechanisms in Arctic **sea ice** can provide memory and thus predictability at **seasonal scales**



Blanchard-Wrigglesworth et al 2011

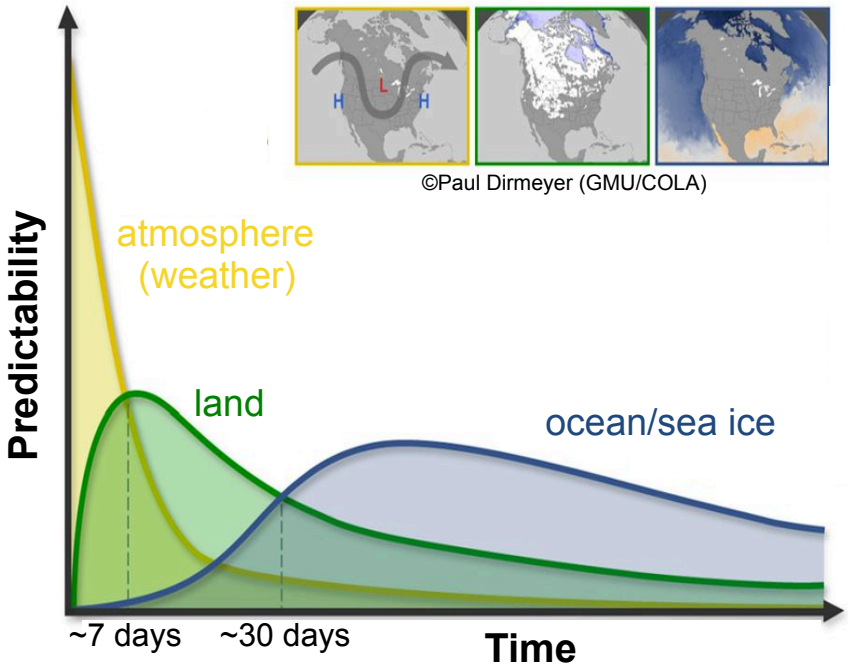
And at longer time-scales Arctic sea ice is experiencing a long-term **decline**

sea ice



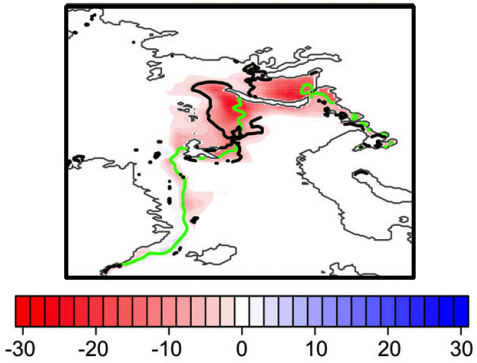
Internal sources of Climate Predictability

Mariotti et al 2018

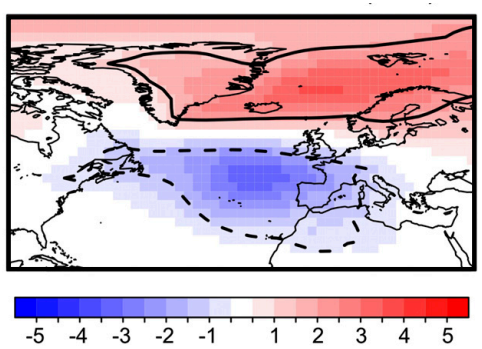


While many studies report **important impacts** of Arctic sea **on the climate of the mid-latitudes**

1st EOF of November Sea Ice Cover (SIC)



Predicted DJF Sea Level Pressure



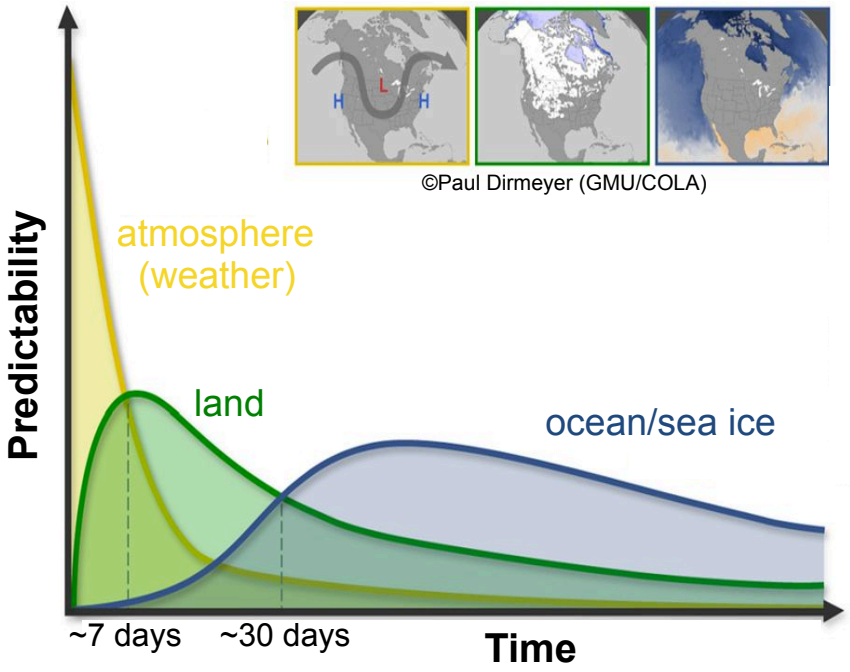
García-Serrano et al 2014

sea ice

For example, on Europe at **seasonal timescales** through an influence of **Barents-Kara Seas** SIC changes on the **North Atlantic Oscillation**

Internal sources of Climate Predictability

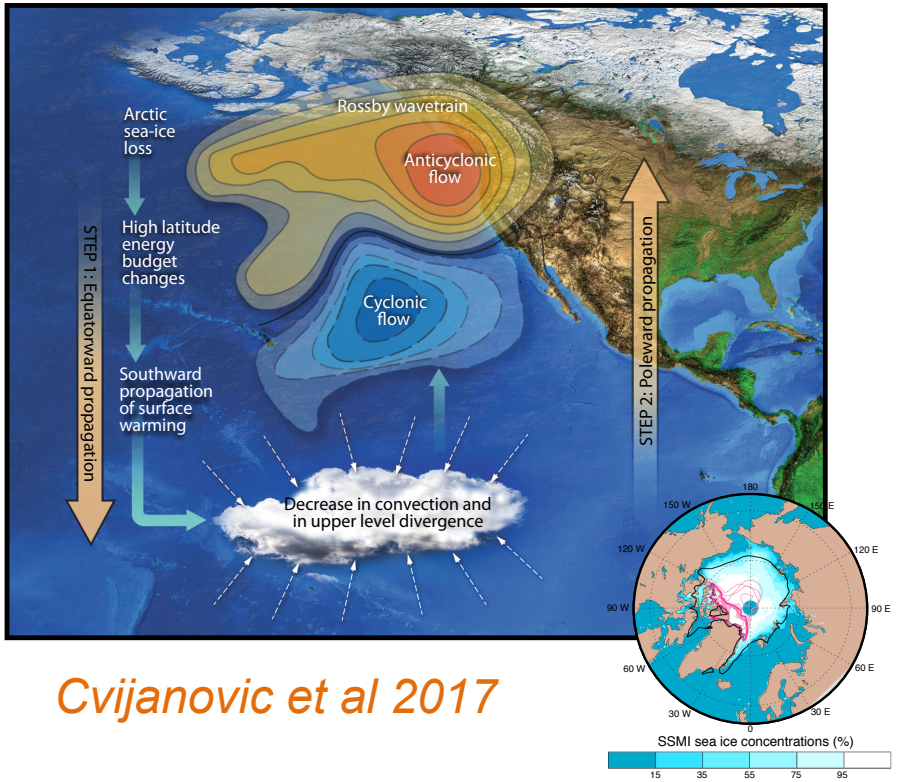
Mariotti et al 2018



sea ice

While many studies report **important impacts** of Arctic sea **on the climate of the mid-latitudes**

Response to Arctic sea ice reduction



Cvijanovic et al 2017

Or even explaining a **long-term intensification of Californian droughts**

Introducing our main prediction tool

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

Model Components

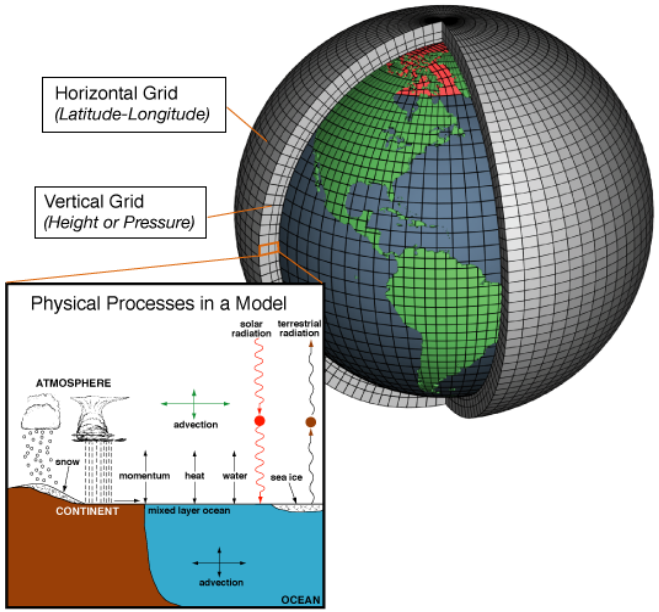
IFS (Atmospheric Model):
T255 (0.75º) ~80km
L91 (top 0.01hPa) ~mesosphere
IFS-HTESSEL (Land Model)

NEMO (Ocean Model):
Nominal 1° Resolution
L75 levels (thousands km deep)
PISCES (Biogeochemistry Model)

LIM (Sea-ice Model):
Multiple (5) ice category

ECMWF Open IFS
IFS-HTESSEL
EC-EARTH 3
LIM
NEMO

EC-EARTH
Global Coupled model



Introducing our main prediction tool

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

Model Components

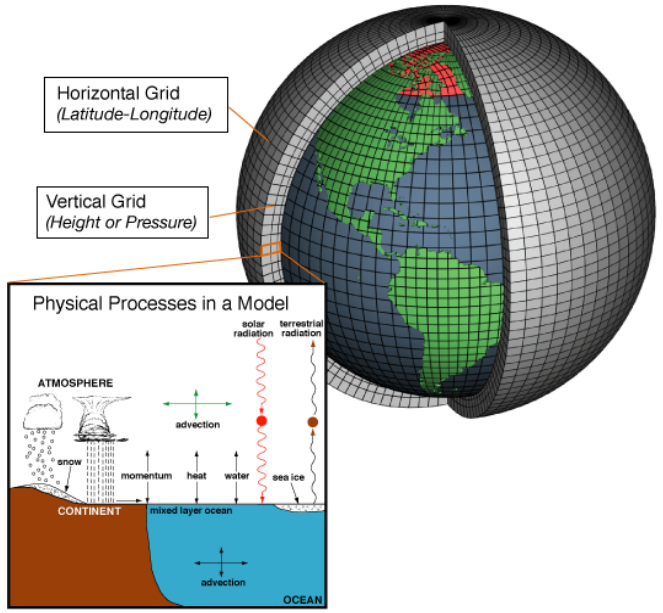
IFS (Atmospheric Model):
T255 (0.75º) ~80km
L91 (top 0.01hPa) ~mesosphere
IFS-HTESSEL (Land Model)

NEMO (Ocean Model):
Nominal 1° Resolution
L75 levels (thousands km deep)
PISCES (Biogeochemistry Model)

LIM (Sea-ice Model):
Multiple (5) ice category

ECMWF Open IFS
IFS-HTESSEL
EC-EARTH 3
LIM
NEMO

EC-EARTH
Global Coupled model



Initial Conditions

produced in-house

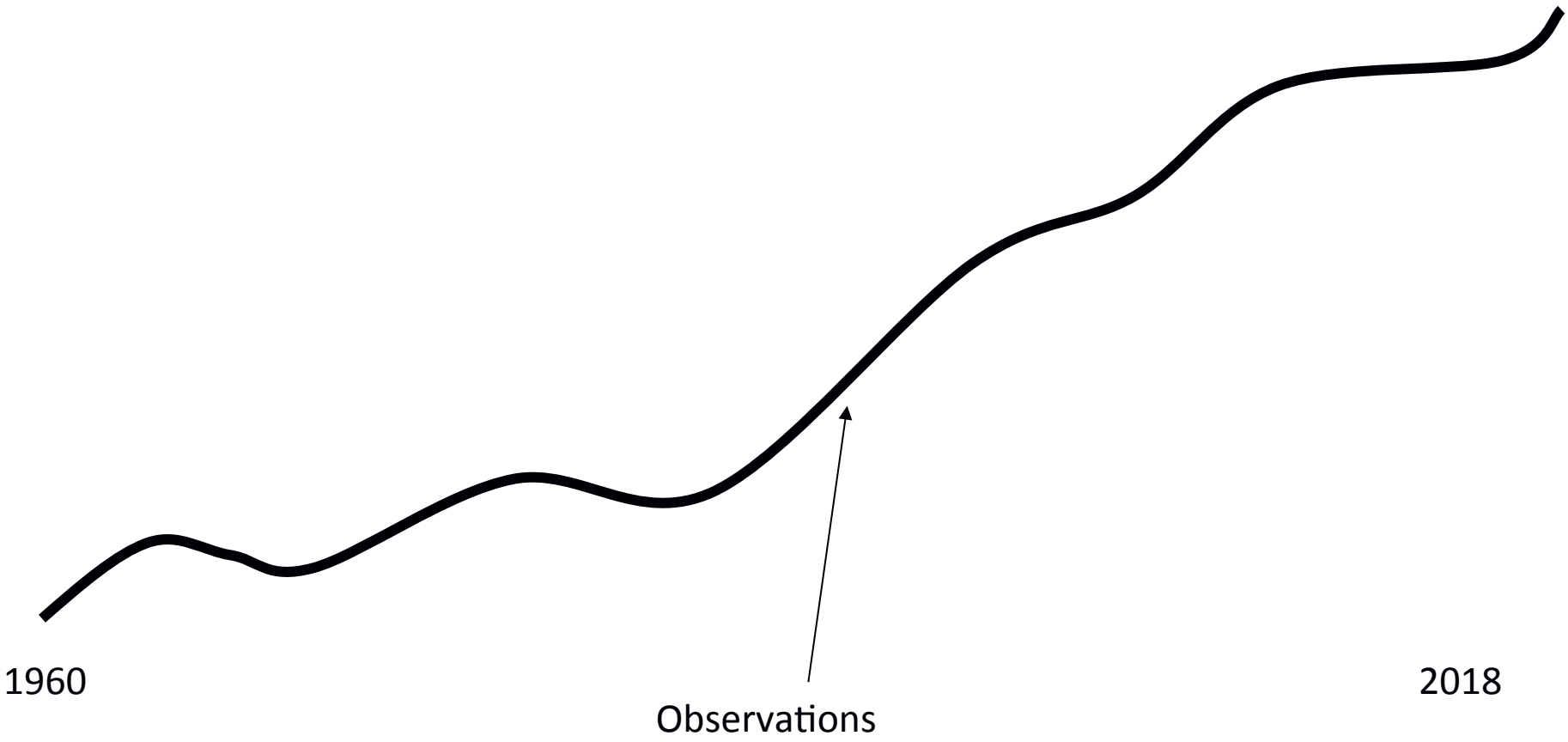
Atmosphere reanalysis (**ERA-Interim**)

Sea Ice reanalysis (**ESA**)

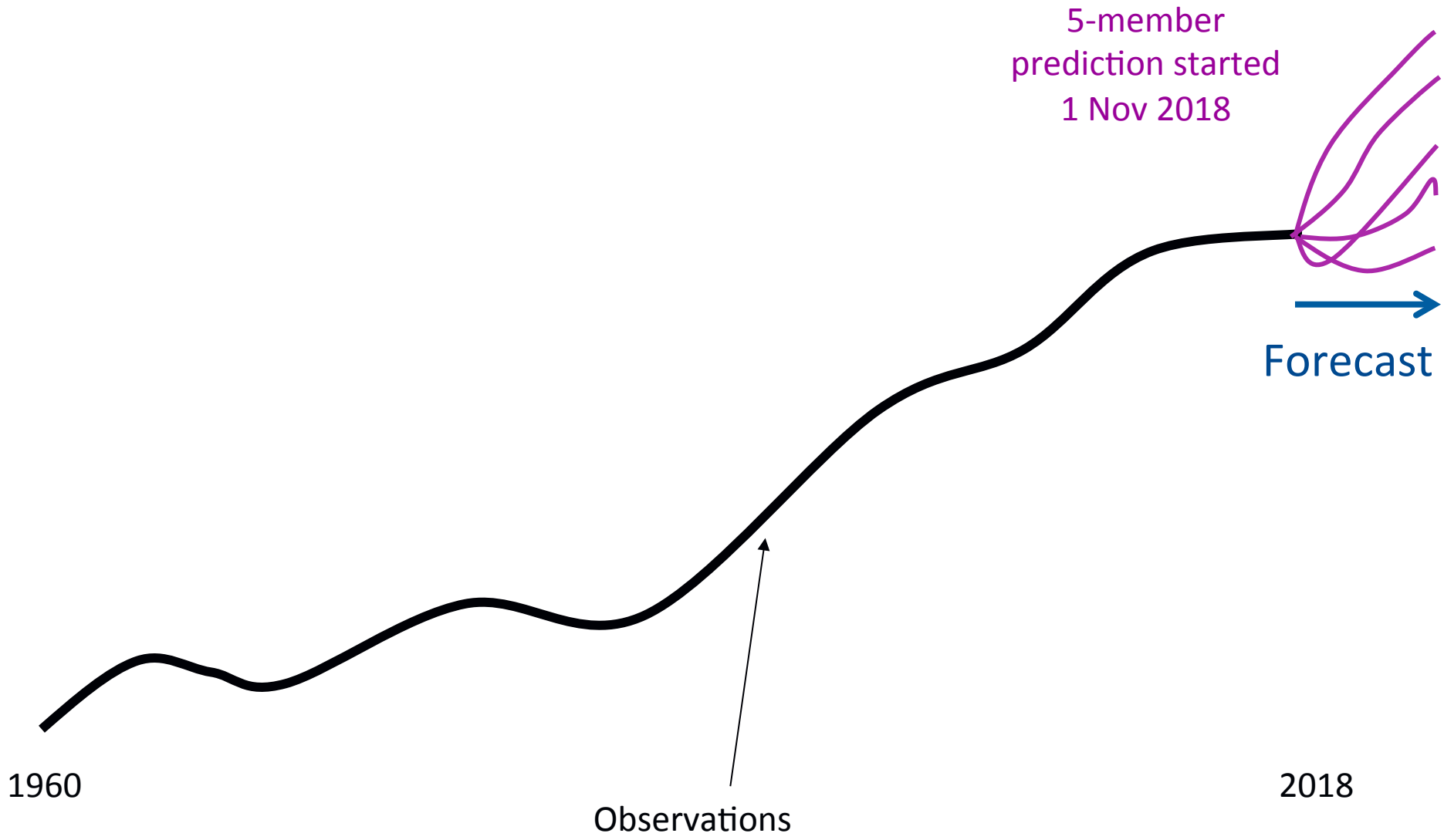
Land reanalysis (**ERA-Land**)

Ocean reanalysis (**ORAS4**)

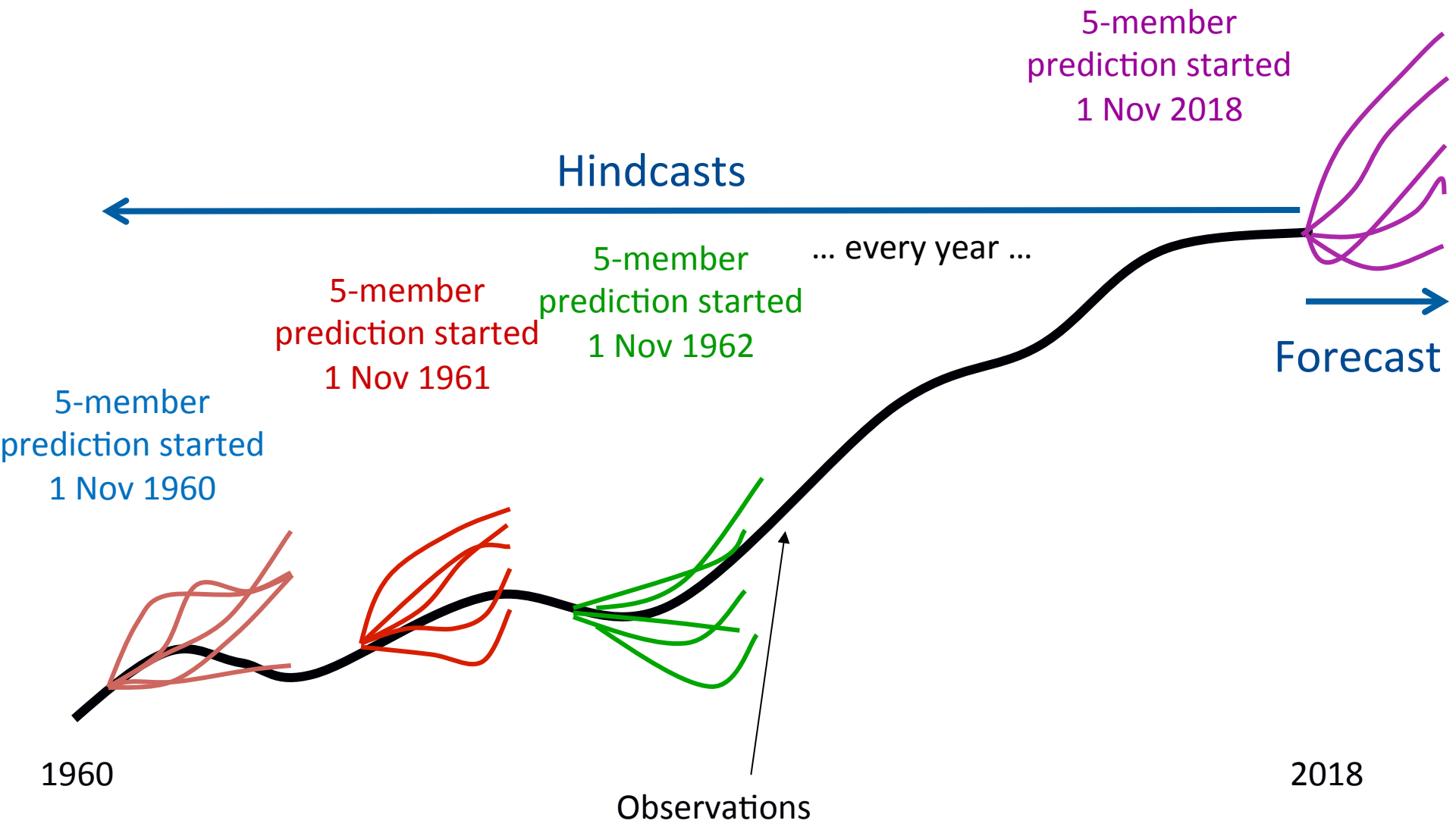
Introduction to Climate Prediction Systems



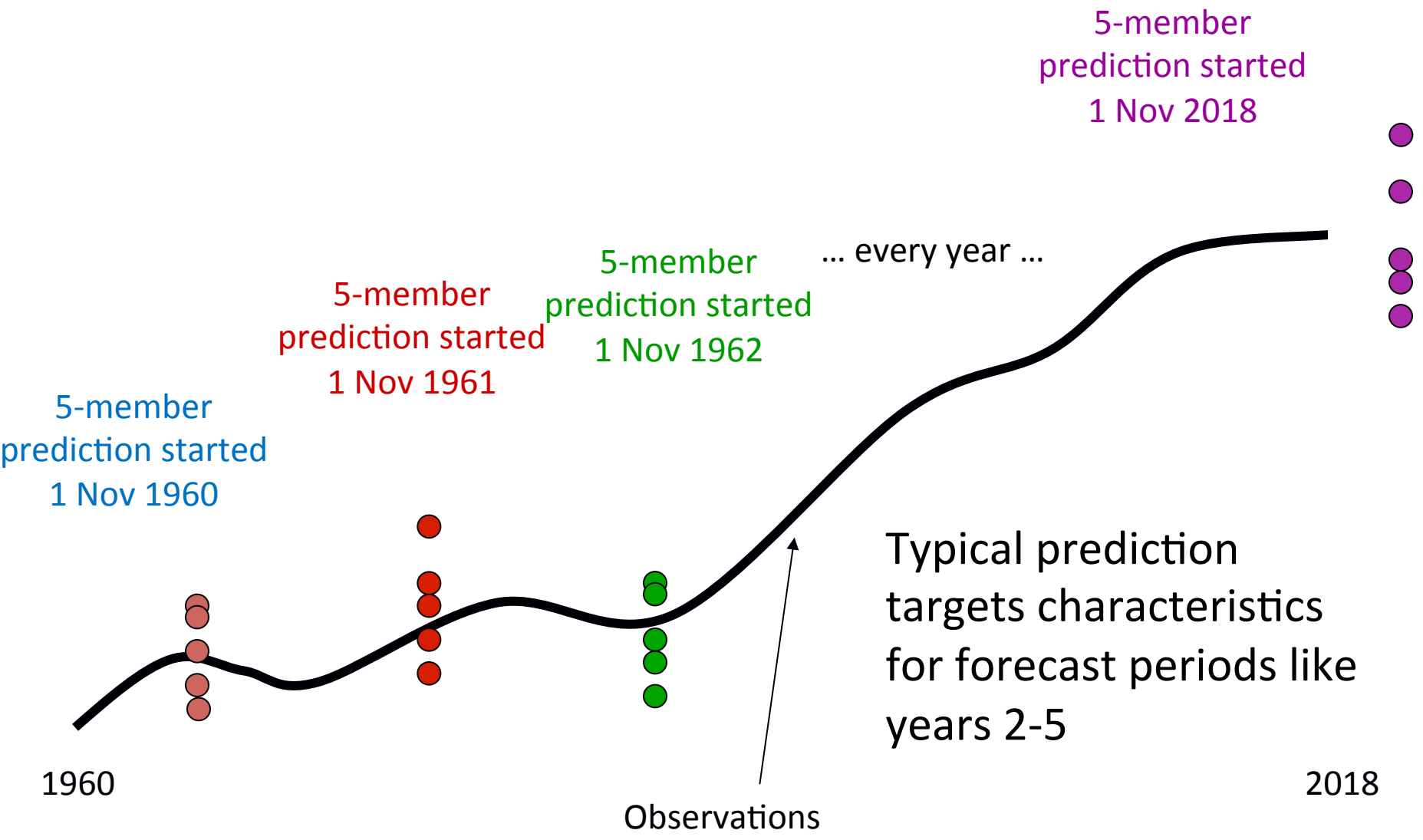
Introduction to Climate Prediction Systems



Introduction to Climate Prediction Systems



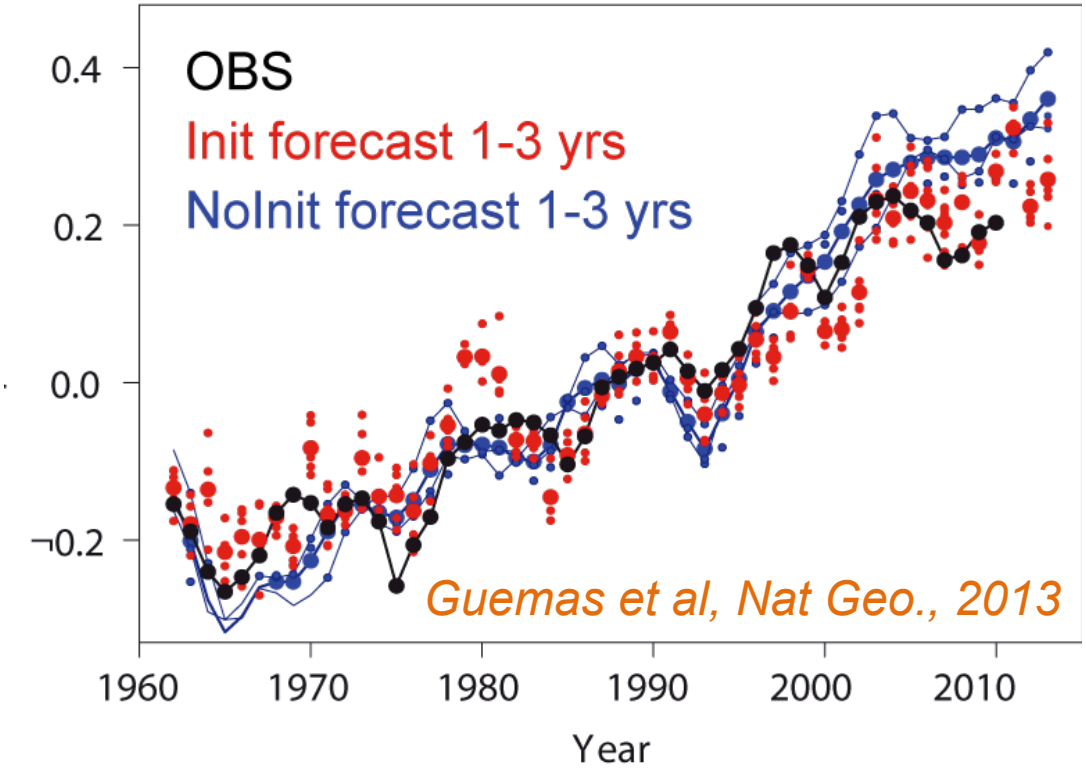
Introduction to Climate Prediction Systems



Two examples in decadal prediction (I)

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

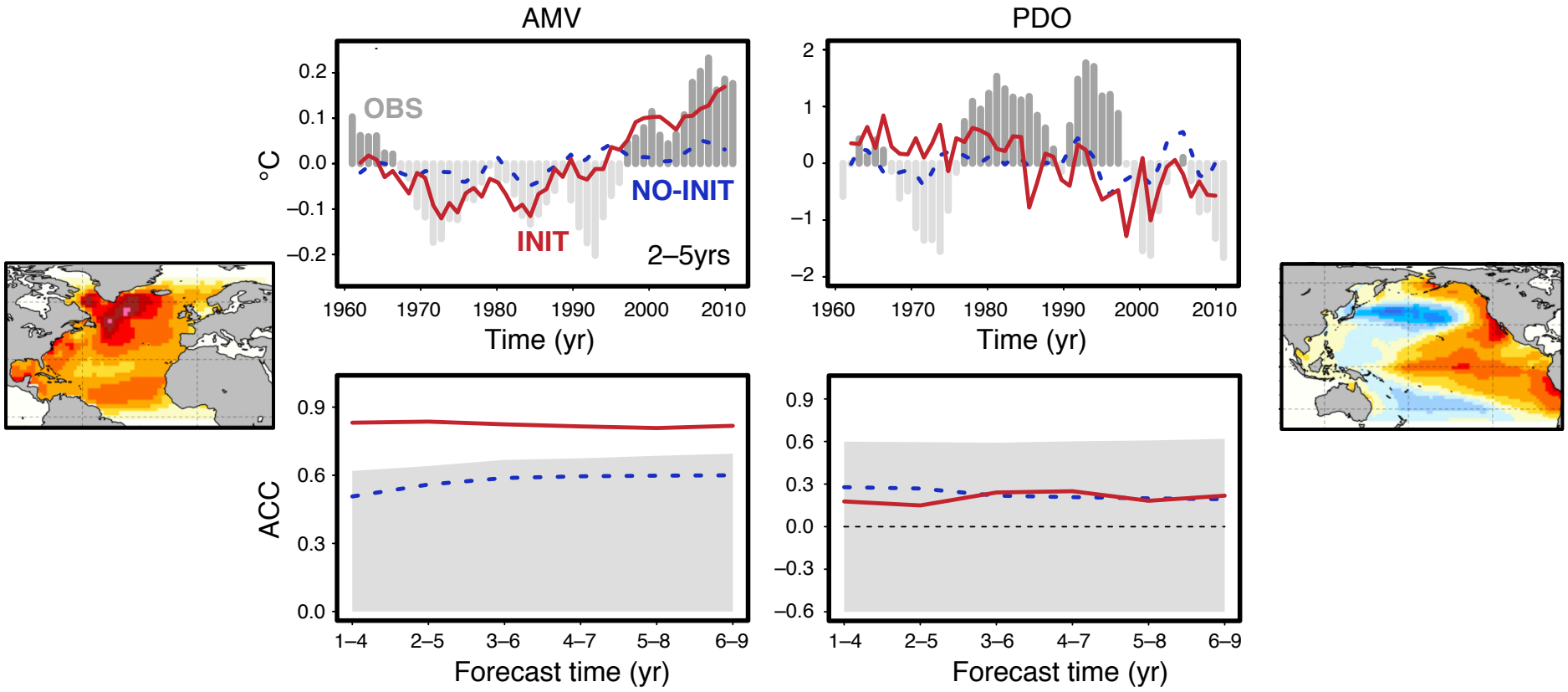
Predictive skill of **global mean surface-air temperature** (Ec-Earth2.3)



Initialised forecasts with EC-Earth reproduce the global temperature, and **describe more accurately** than the non-initialized ones the recent **HIATUS** period, which suggests a **key contribution of internal climate variability**

Two examples in decadal prediction (II)

Predictive skill of **modes of multi-annual climate variability** (in CMIP5)

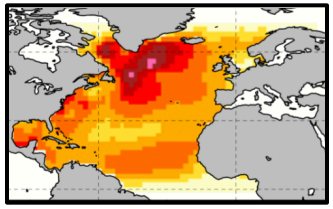


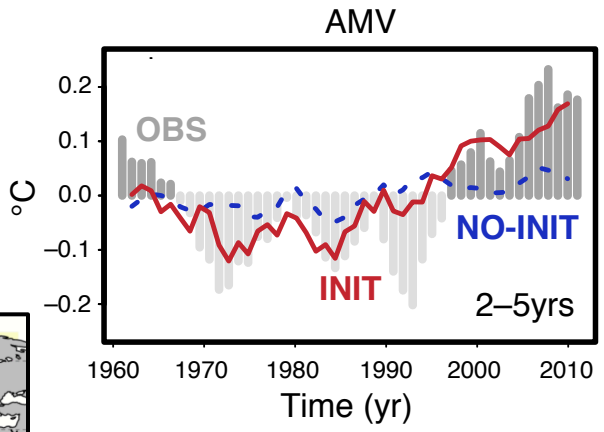
Doblas-Reyes et al, Nat. Comm., 2013

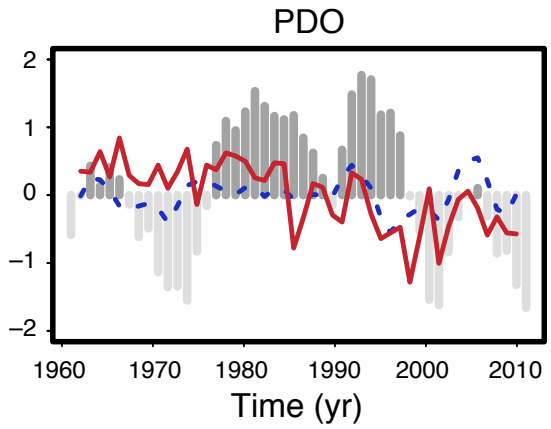
Only in the **Atlantic Ocean**, the **initialized forecasts** show significant **predictive skill** and beat persistence**,** for forecast times of **up to 10 yrs**

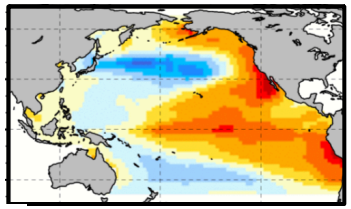
Two examples in decadal prediction (II)

Predictive skill of **modes of multi-annual climate variability** (in CMIP5)

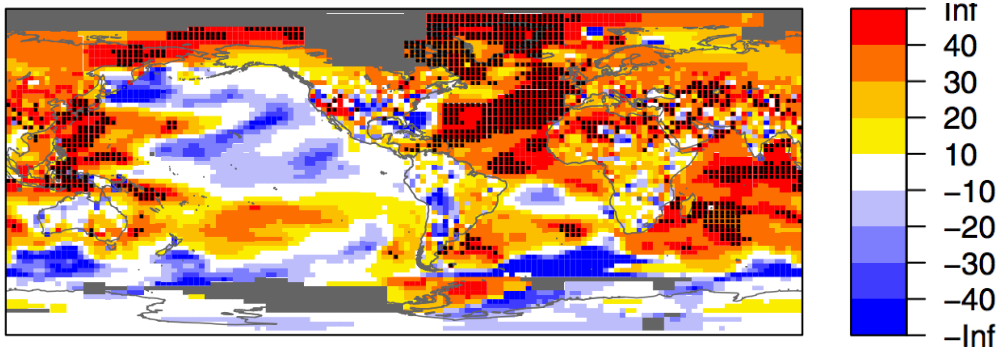








Multi-model skill in SAT 2-5 yrs lead time



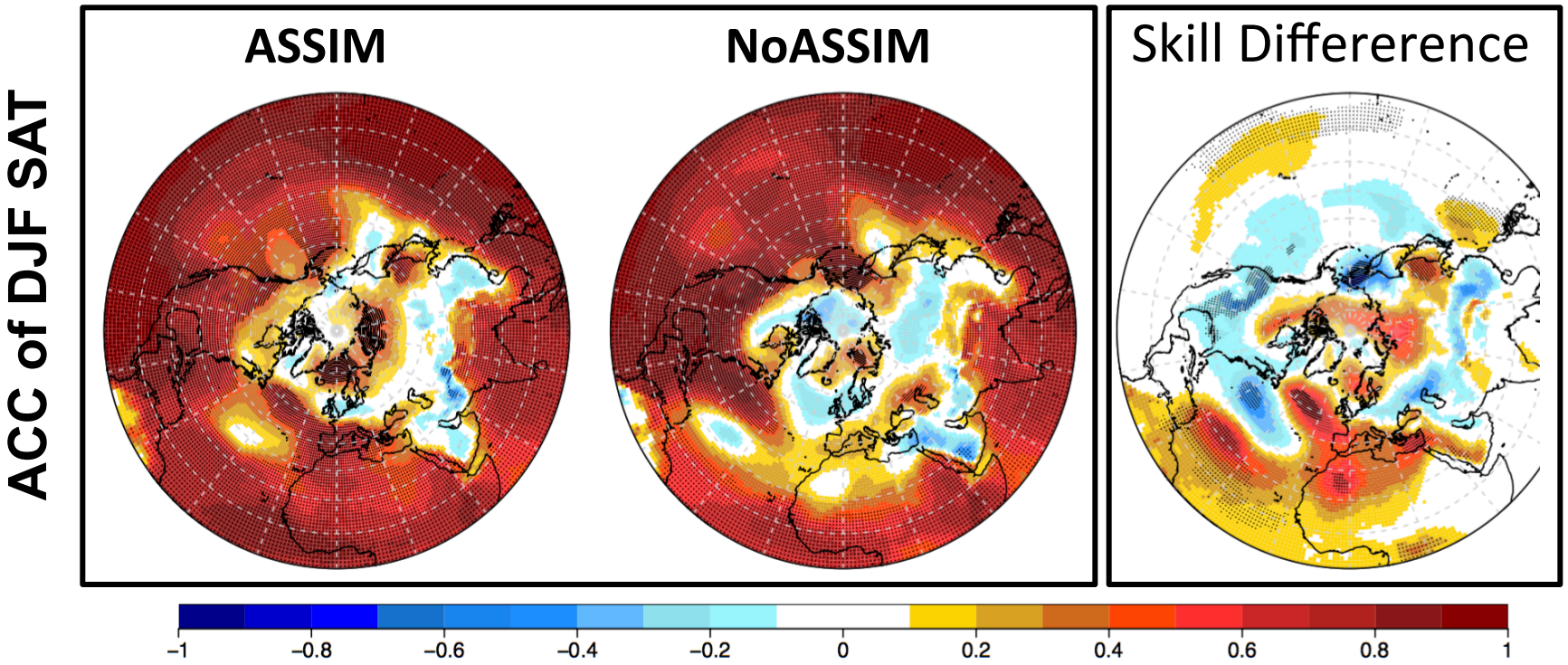
Doblas-Reyes et al, Nat. Comm., 2013

The **grand challenge** of current **decadal prediction systems** is to improve the **predictive** skill over the **continents**

Seasonal Prediction: role of Sea Ice (I)

Two initialization methods for sea-ice (initialized Nov 1st):

1) With assimilation of sea ice concentrations (**ASSIM**)
2) Without assimilation (**NoASSIM**)

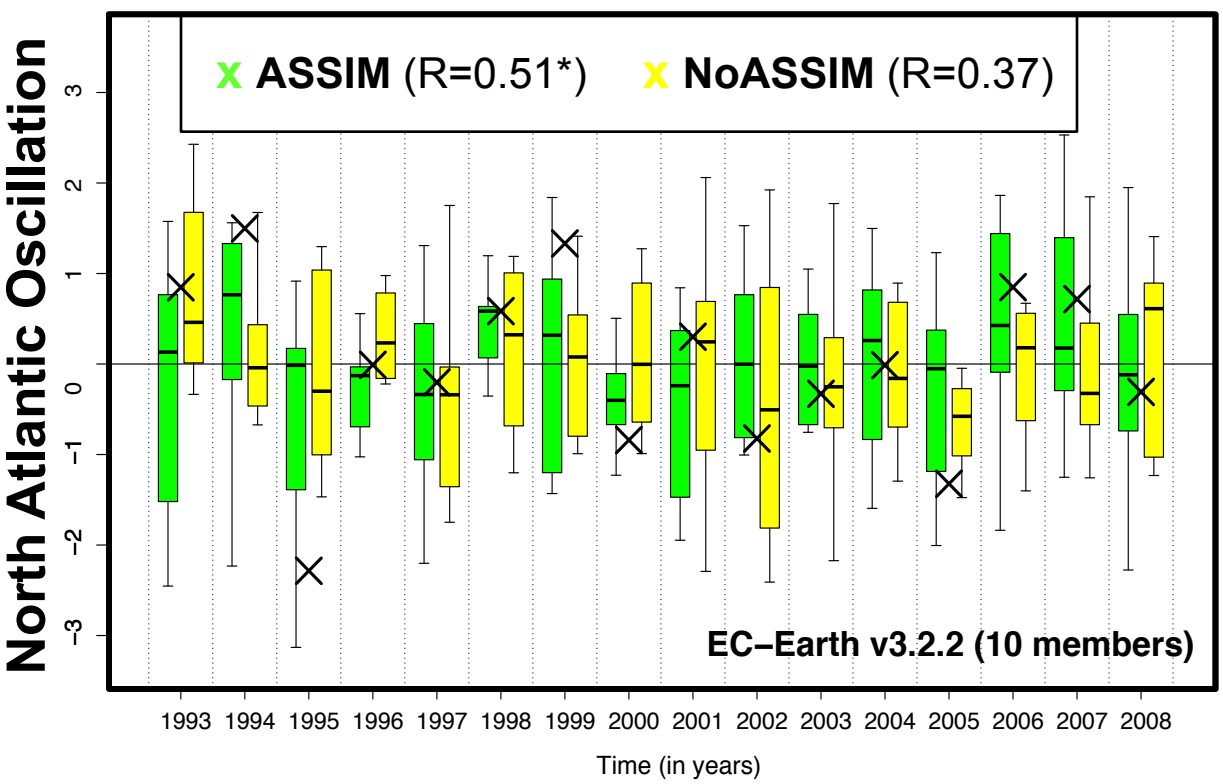


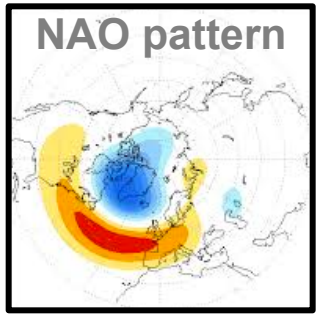
A **better sea-ice** initialization can **improve** the skill in the **Mediterranean area and Scandinavia…**

Seasonal Prediction: role of Sea Ice (I)

Two initialization methods for sea-ice (initialized Nov 1st):

1) With assimilation of sea ice concentrations (**ASSIM**)
2) Without assimilation (**NoASSIM**)





… which might be related to **improved NAO** predictive **skill**

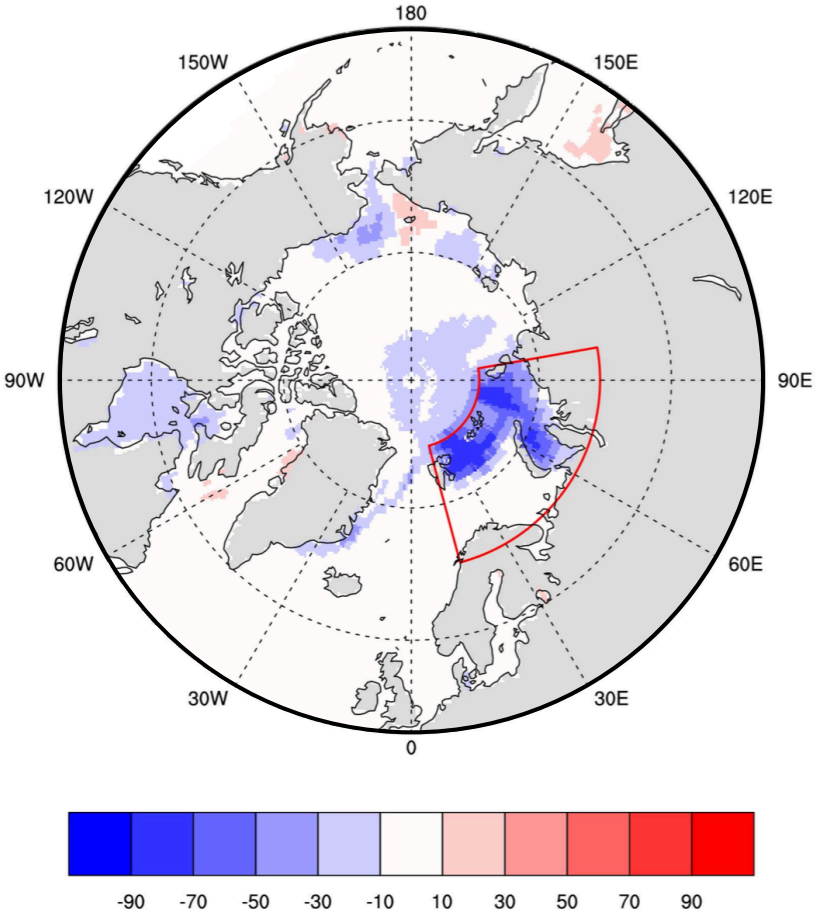
Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

NOV/DEC 2016

Acosta-Navarro et al (2018)

Lowest sea ice cover for those months since 1979

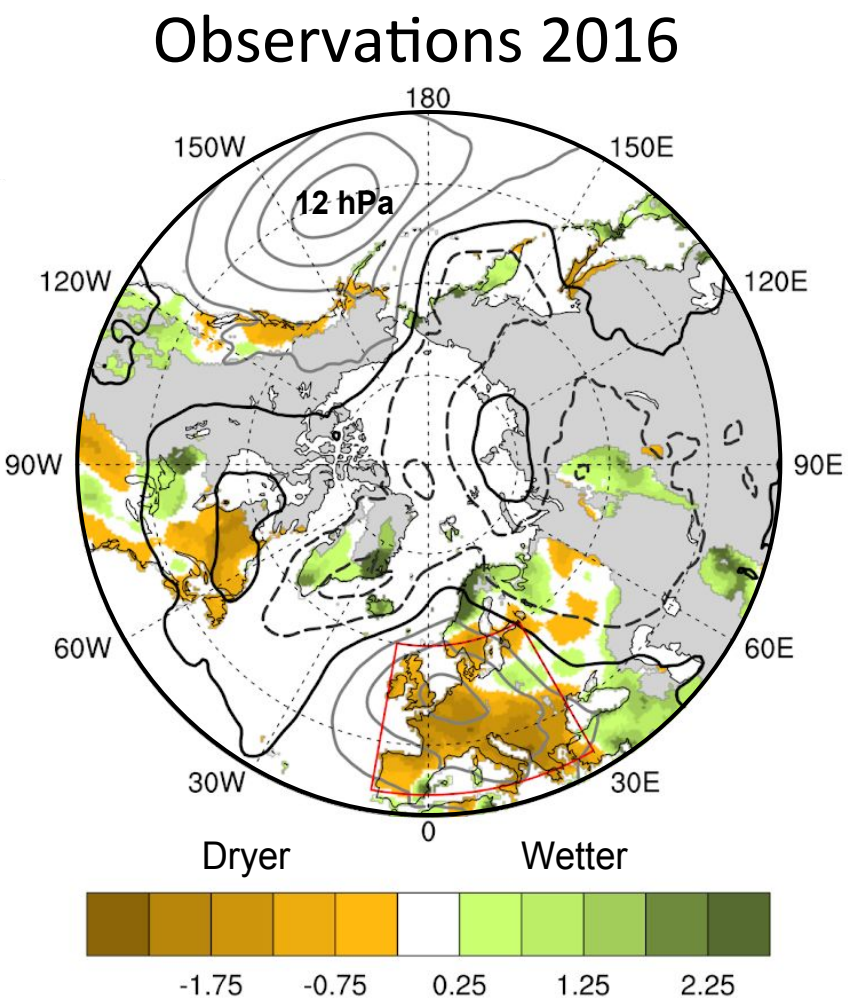
- Largest anomalies in the **Barents** and **Kara** Seas.
- **Important** region for **connecting Arctic** sea-ice with **mid-latitude** climate.



DEC 2016

Acosta-Navarro et al (2018)

Lowest European precipitation in last 116 Decembers

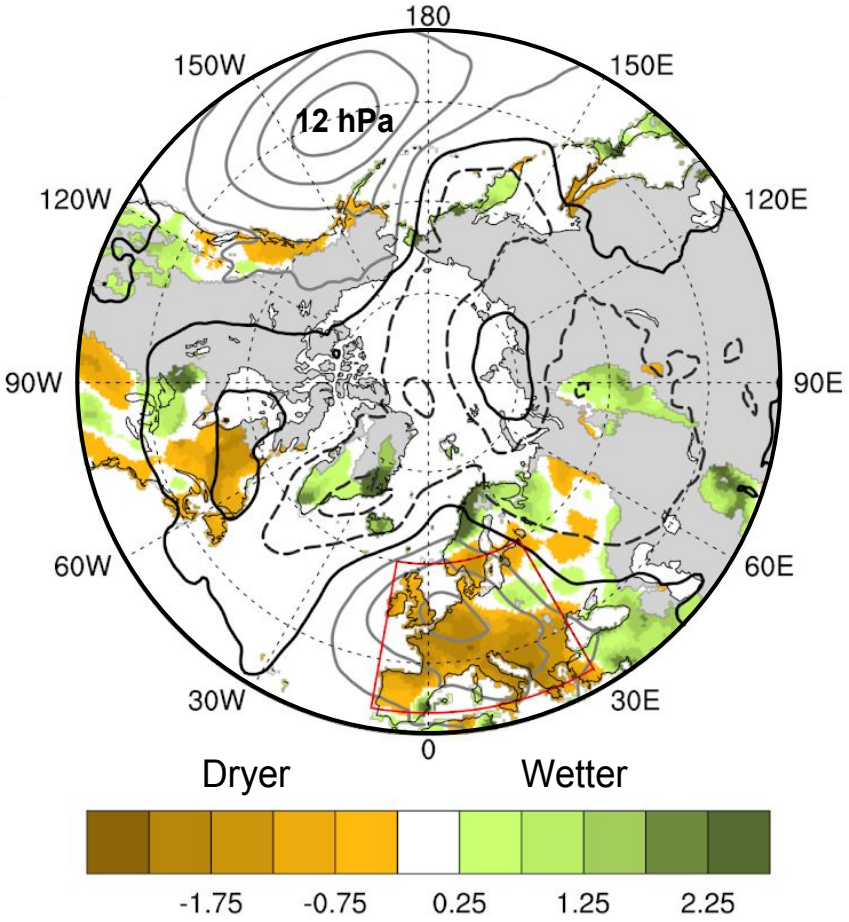


DEC 2016

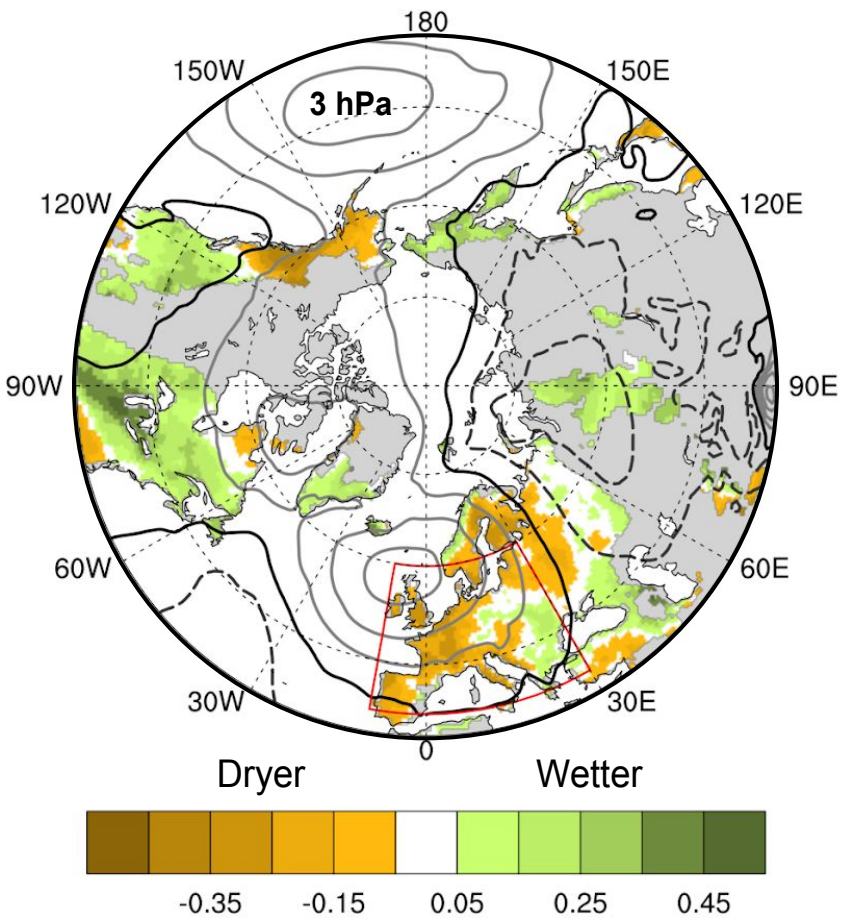
Acosta-Navarro et al (2018)

Lowest European precipitation in last 116 Decembers

Observations 2016



Forecast16 (100 members)

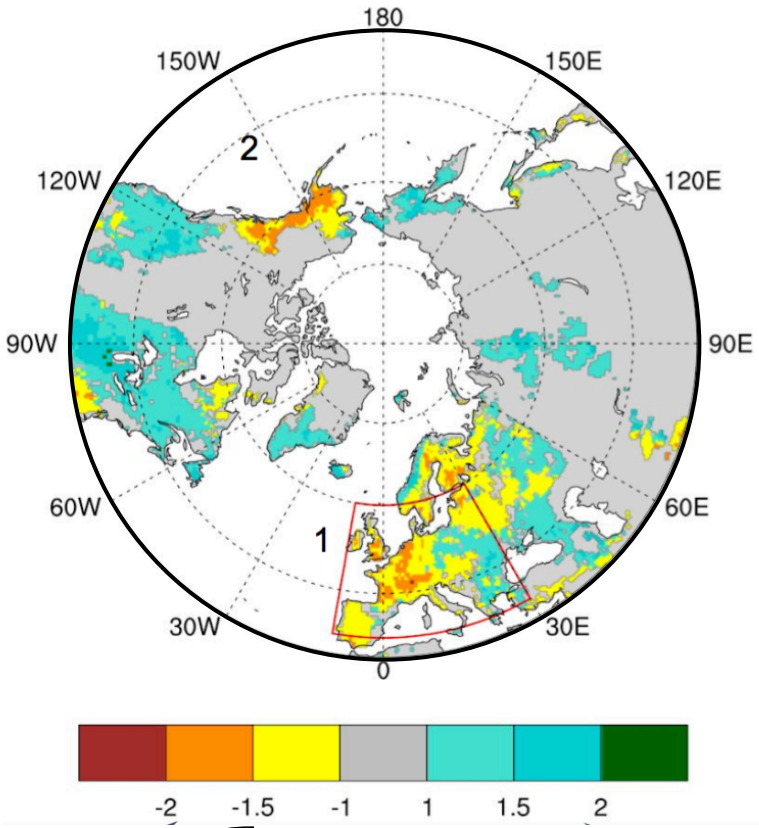


DEC 2016

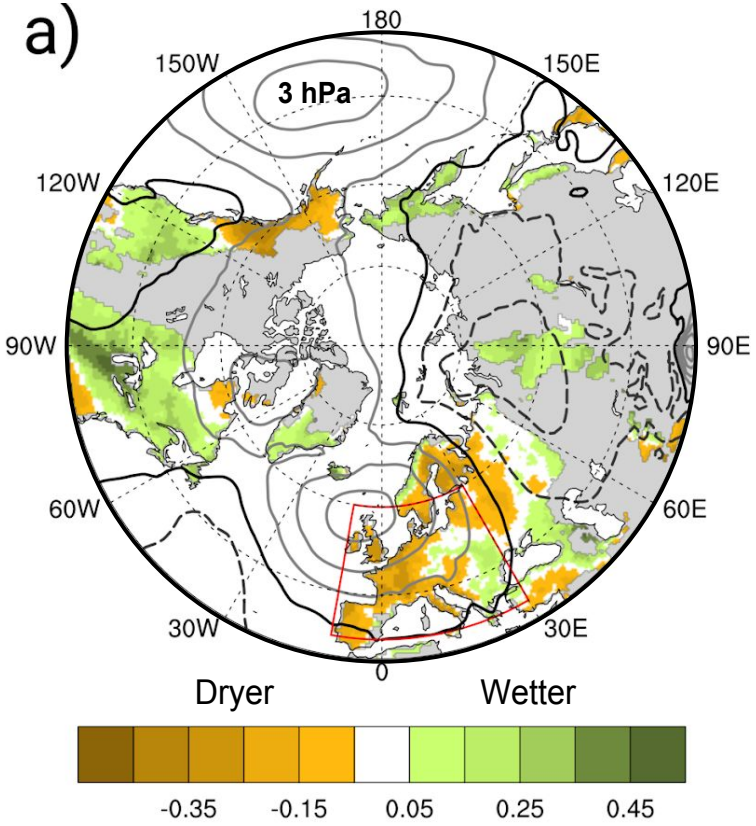
Acosta-Navarro et al (2018)

Lowest European precipitation in last 116 Decembers

Forecast 2016



Forecast16 (100 members)



Odds

Blue/green: higher probability of extreme **wet** conditions

Red/orange: higher probability of extreme **dry** conditions

Seasonal Prediction: role of Sea Ice (II)

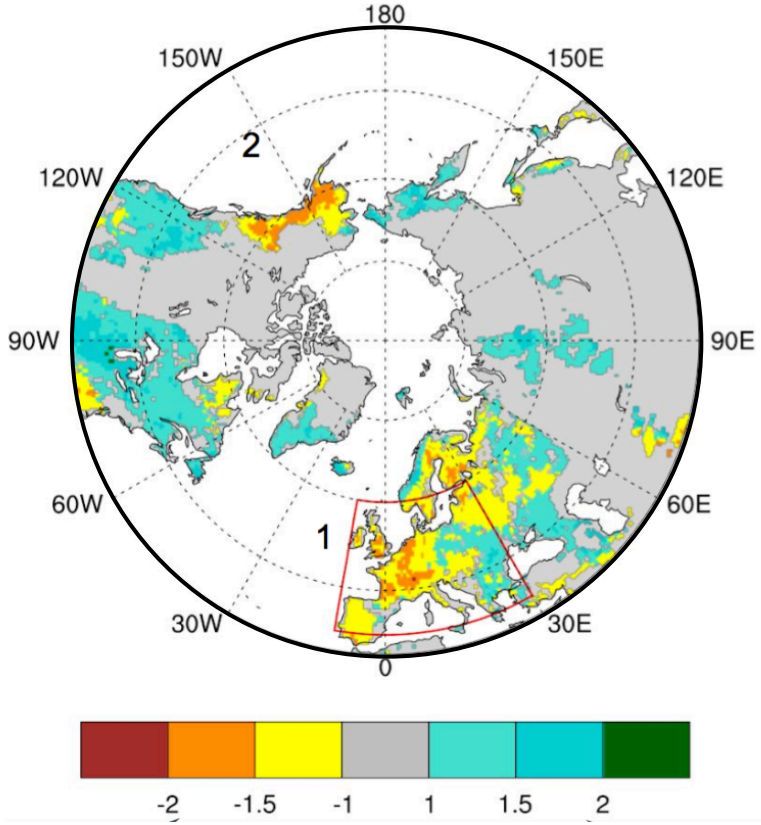
Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

DEC 2016

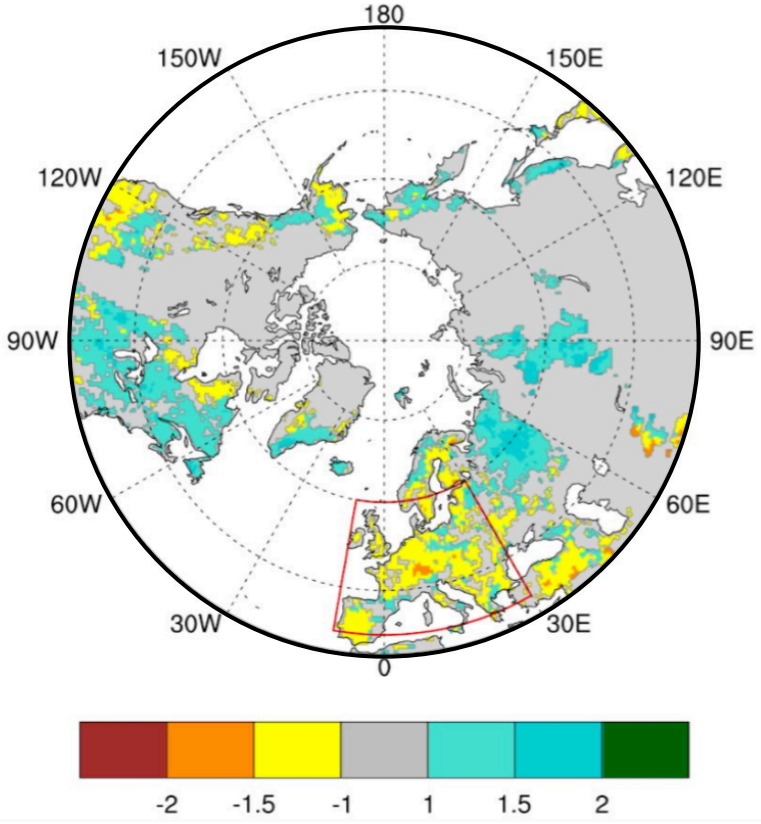
Acosta-Navarro et al (2018)

Lowest European precipitation in last 116 Decembers

Forecast 2016



Forecast 2016 [Sea Ice Clim]



Extreme low rainfall better predicted with correct **low sea ice conditions**

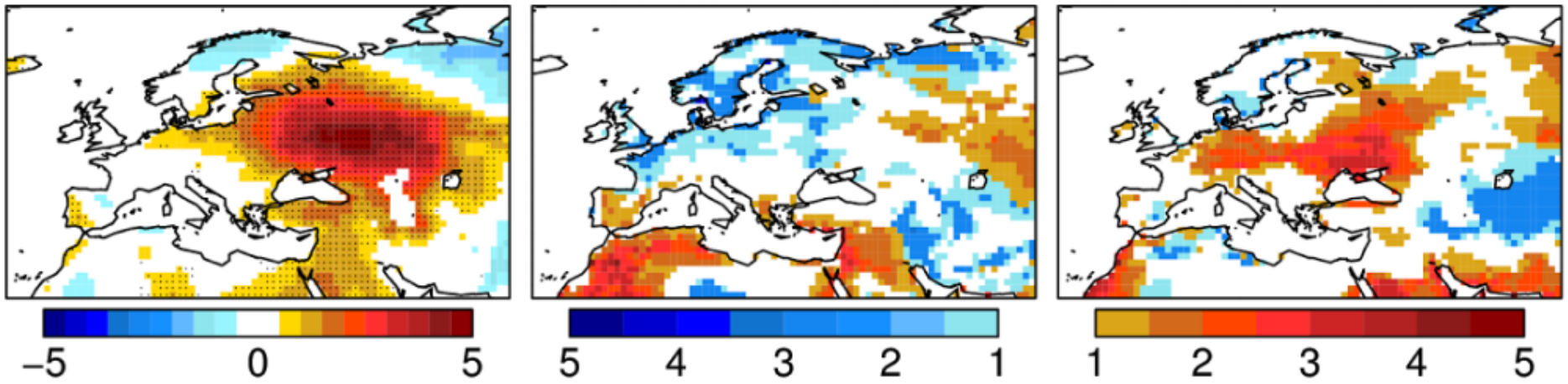
Seasonal Prediction: role of Land Surface

Case study: Heat wave in Eastern Europe during summer 2010

Two seasonal forecasts (initialized May 1st): *Prodhomme et al. (2016)*

1) Climatological Land Surface Conditions (**CLIM**)
2) Reanalysed ERAi-Land Conditions (**REAS**)

Observed JJA SAT | Odds* JJA SAT (**CLIM**) | Odds JJA SAT (**REAS**)



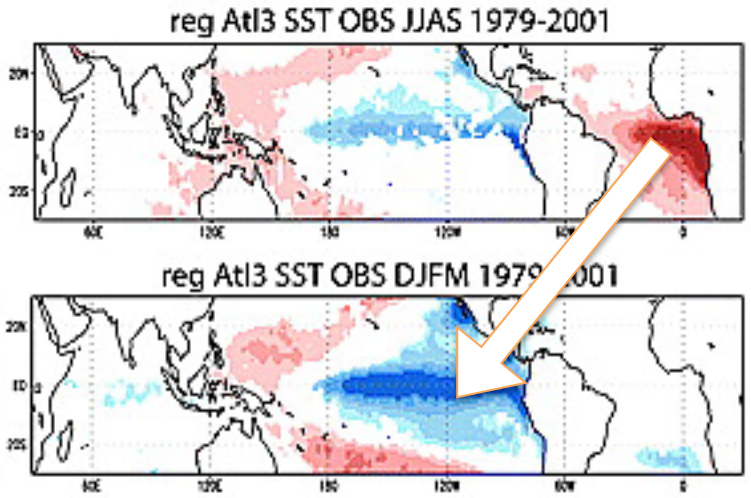
*Odds~Probability of a extreme event to occur wrt climatology

Soil moisture initialization is therefore **essential** for the representation of such **extreme events**

Seasonal Prediction: Interbasin Teleconnections

Rodriguez-Fonseca et al (2009)

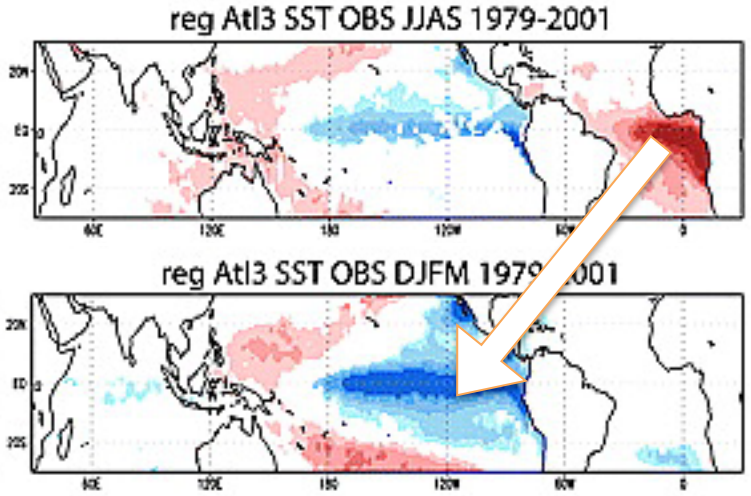
Observed teleconnection of Atlantic Niño with winter NIÑO



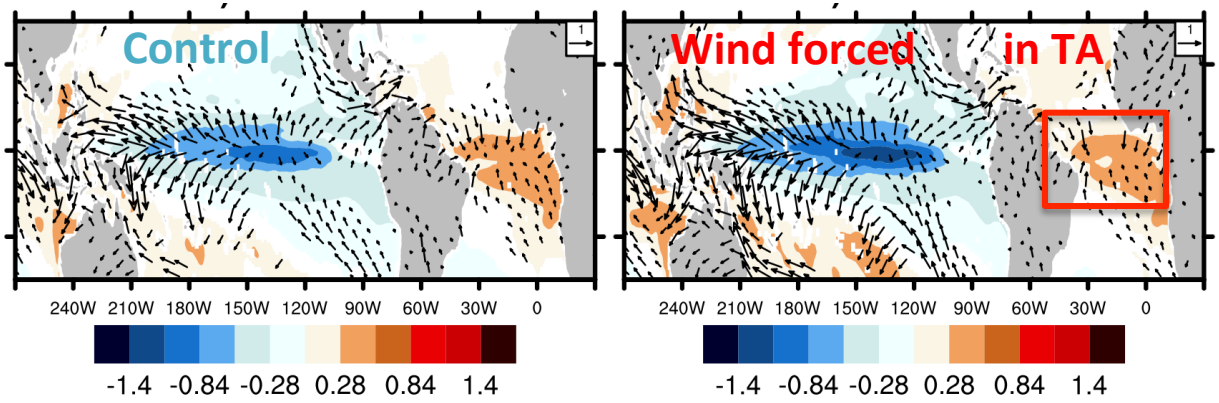
Seasonal Prediction: Interbasin Teleconnections

Rodriguez-Fonseca et al (2009)

Observed teleconnection of Atlantic Niño with winter NIÑO

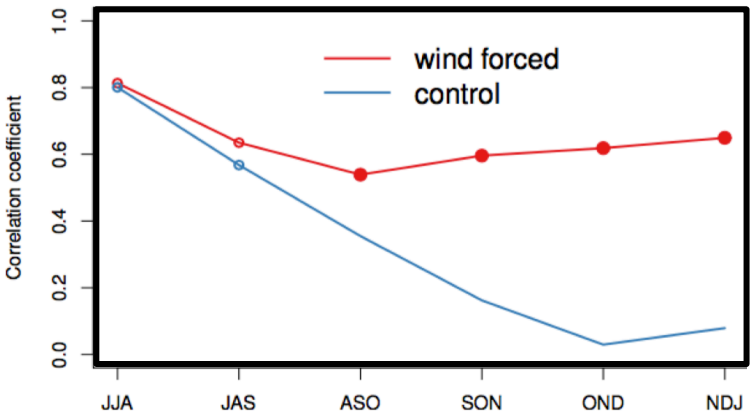


Regression JJA ATL3 vs SON SST

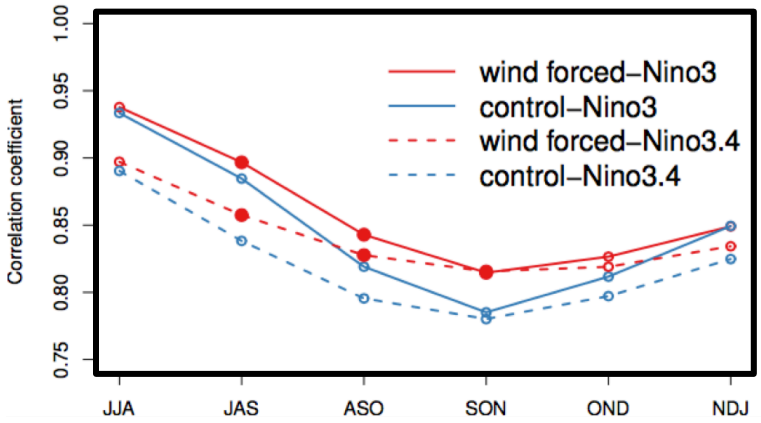


Seasonal Prediction: Interbasin Teleconnections

Skill in ATL3 (1980-2004)

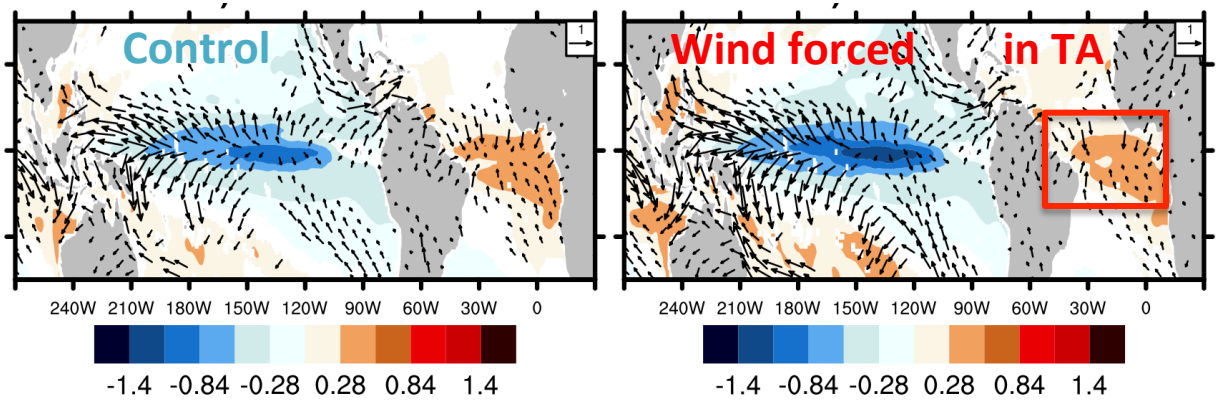


Skill in NIÑO (1980-2004)



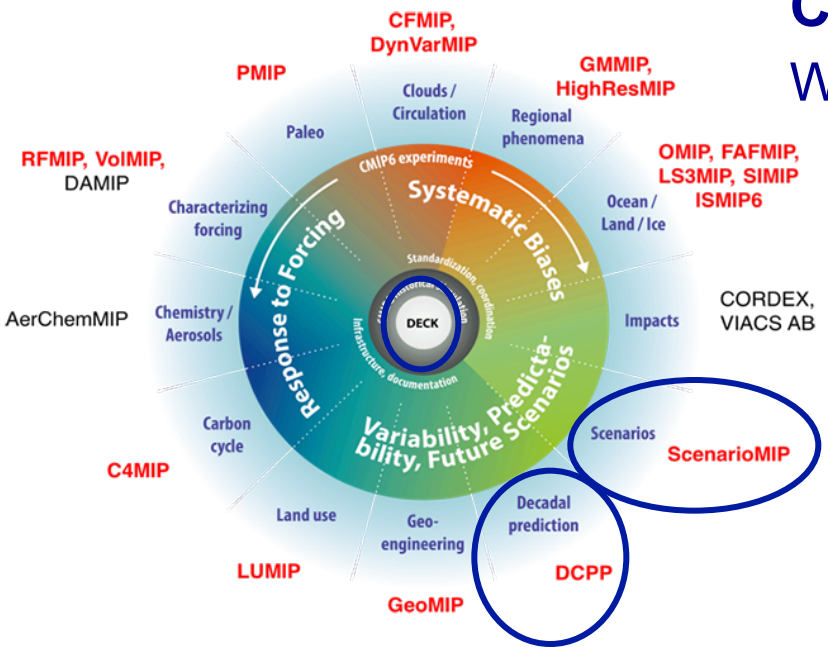
Improved representation of **TA variability** can **lead to better** skill in **ENSO**

Regression JJA ATL3 vs SON SST



Next decadal climate prediction activities

Simpkins (2017)



Contributions to CMIP6

With EC-Earth 3.2 in standard resolution (~1°)

DCPP Component A:
Retrospective Predictions [1960-2017]

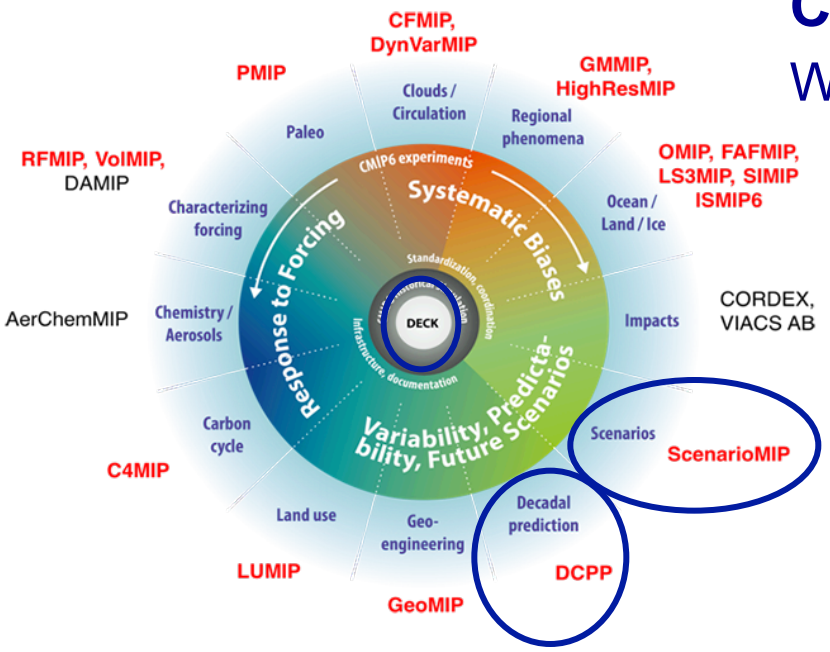
DCPP Component B:
Near-real time Forecasts [2018 onwards]

DECK+ScenarioMIP:
Historical+SPSS2-4.5 [1850-2100]

WCRP CMIP6
World Climate Research Programme

Next decadal climate prediction activities

Simpkins (2017)



Contributions to CMIP6

With EC-Earth 3.2 in standard resolution (~1°)

DCPP Component A:
Retrospective Predictions [1960-2017]

DCPP Component B:
Near-real time Forecasts [2018 onwards]

DECK+ScenarioMIP:
Historical+SPSS2-4.5 [1850-2100]

WCRP CMIP6
World Climate Research Programme

Other H2020 activities

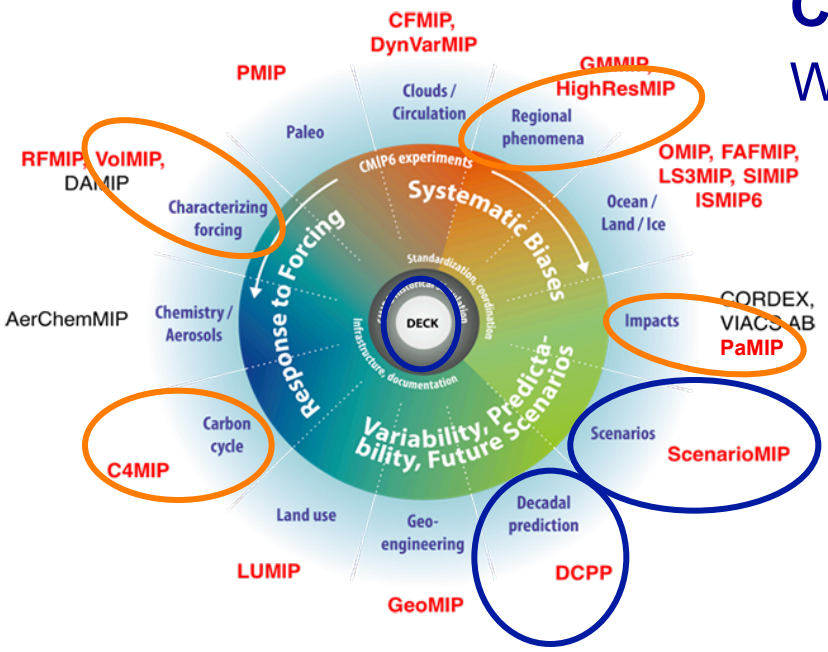
With EC-Earth 3.2 in high resolution (~0.25°)

EUCP
European Climate Prediction system

DCPP Component A-like:
Retrospective Predictions [1960-2017]

Next decadal climate prediction activities

Simpkins (2017)



Contributions to CMIP6

With EC-Earth 3.2 in standard resolution (~1°)

DCPP Component A:
Retrospective Predictions [1960-2017]

DCPP Component B:
Near-real time Forecasts [2018 onwards]

DECK+ScenarioMIP:
Historical+SPSS2-4.5 [1850-2100]

WCRP CMIP6
World Climate Research Programme

Other CMIP6 contributions

VolMIP: Evaluating the predictability associated to volcanoes

C4MIP: Investigating the predictability of the carbon cycle

HiResMIP: Determining the advantages of super high resolution (1/12°)

PaMIP: Constraining the long-term impacts due to Arctic Sea Ice decline

PRIMAVERA
APPLICATE.eu

Take-home messages

Climate Prediction relies on the **proper initialization** of regions with internal seasonal to multi-annual climate variability, usually associated with **persistence and memory** in the **ocean**, **land cover**, **sea ice** and even the **atmosphere**.

Forecasting **extreme events** on mid-latitudes can be substantially improved with better initialization of **sea ice** and **surface moisture**

Major challenge of decadal prediction systems is to **improve** their skill **over the continents**

Coordinated prediction efforts, like the multi-model decadal predictions within CMIP6, will provide an invaluable framework to:

- identify the **regions/variables robustly predictable**

- better **understanding** the origin of **systematic errors**


Thank you!
pablo.ortega@bsc.es
BSC
Barcelona
Supercomputing
Center
Centro Nacional de Supercomputación